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Sampling Techniques for CA Quality Assurance

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Statistical Process Control for Evaluating Contract Service at Army Installations

by
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Many Real Property Maintenance Activities at Army installations are performed on a contract basis and represent a major portion of the Directorate of Engineering and Housing (DEH) budget. The wide range of services rendered in support of the installation has made the DEH function increasingly complicated--especially in quality control. Typically, an inspector checks a random sample of the contractor's work and tallies quality in terms of percentage passed versus failed with respect to contract standards.

Due to constraints on funds and inspector availability, some installations have used statistical evaluation methods to estimate service quality. However, both the Army and the contract community have been dissatisfied with the results obtained from these methods. The Army sees no inherent protection for the consumer (i.e., the installation), whereas many contractors complain that their failure risk is too high.

Statistical process control has been compared with two other approaches (confidence intervals and acceptance testing) to determine the potential for this technology in developing realistic sampling plans that offer equal protection for both consumer and producer. These theories were first assessed from a practical standpoint and then were subjected to experimental manipulation using a computer simulation program.

Results showed that the optimal solution is to use a combination of process control (the p-chart method) and acceptance testing (Military Standard 105D) to evaluate service quality. This approach offers realistic output that protects the consumer and producer at a similar level; in addition, process control allows historical data to be used so that a contractor who has performed well in the past can be sampled less stringently. Finally, a major advantage is that overall quality of contract services should improve by implementing this approach because the contractor will receive feedback that identifies inconsistencies in services performed; the faults can then be corrected and, over time, the contractor will learn what needs to be done to provide acceptable performance.

A step-by-step implementation plan has been proposed. It is recommended that the Army field-test this approach and develop an automated system for rapid evaluation.

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FOREWORD

This work was performed for the U.S. Army Engineering and Housing Support Center (USAEHSC) under Project 4A162734AT41, "Military Facilities Engineering Technology"; Technical Area C, "Operations, Maintenance, and Repair"; Work Unit 059, "Sampling Techniques for CA Quality Assurance." G. Cromwell, CEHSC-FM, was the USAEHSC Technical Monitor.

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1 INTRODUCTION

Background

Service contracts represent a sizable expense at U.S. Army installations and deal with activities ranging from janitorial services to minor construction. The activities are characterized by their great variety within and among contracts. To ensure that services are performed according to the standards specified in the contracts, installation Directorates of Engineering and Housing (DEHs) increasingly applied formal procedures for controlling the quality of services--a function complicated by the wide range of activities.

Some DEHs have used statistical techniques based on acceptance sampling plans similar to those in Military Standard 105D (the ABC standards).[1] The contract stipulates an Acceptable Quality Level (AQL) corresponding to an acceptable producer's (contractor's) risk that a lot (contract) will be rejected when the percent defective in it is at or below the AQL. An appropriate sampling plan is then selected from standard sampling tables and applied to evaluate the work delivered.

Both the Army and its contractors have had serious concerns about these plans. The Army does not see an explicit provision for the consumer's (Army's) risk of accepting inferior contracts. In fact, inferior quality has not been defined and an acceptable risk has not been stipulated. Contractors have objected when the Army has attempted to make deductions from payments after a task was rejected on the basis of a sample. Some of these objections stemmed from claims that sample sizes were too small and the producer's risk too high. It was concluded that the MIL-STD-105D plans alone are not adequate for controlling the quality of service activities (as will be shown theoretically in Chapter 4).

Another important factor influencing quality monitoring is inspection effort. Installations suffer from a shortage of qualified inspectors and from the tremendous workload exerted on their inspection teams. Therefore, while reliable discrimination between acceptable and rejectable contracts calls for large sample sizes, the constraints of economy and inspector availability demand a limit on sample sizes.

The Army's ultimate goal is to acquire the highest quality service from its contracts at minimal cost. Accordingly, it is in all parties' interest to place the burden of quality improvement on the contractor's performance rather than on the inspection process. With high-quality work, the inspection burden will be reduced and most of the correction costs avoided. Thus, the Army needs a quality control (QC) system that addresses these aspects of service contracts.

Clearly, a system that helps diagnose and correct the sources of error in performance would have a role in improving the quality of work delivered by the contractor. Process control techniques, which help identify whether a process is in or out of control, provide such an opportunity. This report evaluates the

[1] Military Standard (MIL-STD) 105D, *Sampling Procedures and Tables for Inspection by Attributes* (Department of Defense, 20 March 1964). Research was conducted using MIL-STD 105D; however, the standard has been updated; MIL-STD 105E, 10 May 1989.

use of process control technology as a more realistic method for determining susceptibility of the work being performed. An example of this method is the form for p-chart application to be used in conjunction with their acceptance sampling tables.[2]

Among the different approaches for service quality control, process control appears to be a promising option. Process control methods could work within the standard Government/contractor role definitions. Although it is the contractor's responsibility to control the process, the Government could provide helpful input, including advice on using process control techniques, guidance as to where contractors can learn the techniques, and feedback of relevant information collected and analyzed by the government. This approach should benefit both parties.

Objective

The objective of this work is to compare process control technology with other statistical QC methods to determine the potential for developing more realistic sampling plans than are now available. These plans should specify optimal conditions for pro rata deductions and equitable contractor/Government protection. If this approach is determined to be feasible, the secondary objective is to recommend a plan of action to help the Army implement these methods in service contracts.

Approach

The study approached the problem in the following ways:

1. Investigated alternative statistical techniques for controlling service contract performance quality, including those now in use at military installations. Both product and process control technologies were evaluated.

2. Assessed the techniques based on several criteria, including ability to provide acceptable producer and consumer risks with minimal inspection requirements. This assessment involved:

- Theoretical evaluation

- Experimental analysis through a computer simulation program.

3. Based on the findings in 1 and 2 above, recommended procedures for military application and proposed an implementation strategy to ensure service quality and enforce high standards of performance.

Scope

In this report, the term "quality control" is used in a broad sense to cover both the traditional "quality assurance" function of the consumer (the Government) in accepting or rejecting a product or service and the function of monitoring the performance of the producer (the contractor). Although this report

[2] H. F. Dodge and H. G. Romig, *Sampling Inspection Tables--Single and Double Sampling*, 2nd ed. (John Wiley and Sons, 1959).

addresses direct advantages of process control to the Government, it is also recognized that the information flow generated can contribute to improvement of producers' performance without interfering in their operation.

Mode of Technology Transfer

It is anticipated that the results of this study will be incorporated into guidance from HQUSACE on developing and administering commercial activities (CA) contracts for the services. The approach will be incorporated into future CA contracts and into quality assurance plans.

2 SERVICE QUALITY CONTROL: SURVEY OF METHODS

Current quality assurance schemes used at military installations were studied. This survey included selection and classification of typical services contracted at a given site; the standards and techniques used to analyze service quality; and typical lot and sample size parameters employed within installations (to become input to the theoretical and experimental analyses described later). The methods studied have some common characteristics in terms of measurement and control of quality and possible faults; these properties are described first to provide background information.

Measurement and Control of Service Quality

Definition of Quality

There are many definitions of quality, but the one that best fits the widest variety of situations, including service operations, is given by Taguchi:[3] "The quality of a product is inversely related to the loss it imparts to the consumer." In simpler terms, the quality of a product or service can be measured by how well it meets specific functional requirements during its life cycle. A common measure of quality based on this concept is the functional variability among similar products. The smaller the variability is, the higher the quality. Applying this definition to the service function, quality is related to the losses imparted to persons in contact with a system which is maintained or serviced improperly. This type of definition has to be elaborated further in measurable terms.

Within military installations, the quality of a service is specified in manuals and/or the contract between the Government and the contractor. It is defined either in terms of the final results or the steps needed to reach the final results. An example of the end-result type of specification is the repair of an air-conditioning unit. The unit can be inspected from a functional standpoint, in which it is simply turned on to see if it operates properly. It could also be inspected at the component level (e.g., the inspector checks whether the filter has been replaced).

An example of a service specification given in terms of the tasks required is provided in the Redstone Arsenal (Huntsville, AL) Maintenance, Repair, and Custodial Services Document (DAAH03-83-C-0049) which contains a complete list of jobs to be performed and in some cases how to do them. For example:

> Venetian blinds shall be cleaned by damp dusting at the frequency indicated ... window shades shall be dry-cleaned with vacuum equipment or treated dry cloths only.

It is generally easier to verify quality in the end product than in the steps leading to it unless the steps are monitored adequately--an activity that can be quite costly and is therefore rarely undertaken.

In general, it is more difficult to define service quality than it is for product quality. Many factors contribute to this problem, including:

1. The difficulty of defining concrete measures of service and the subsequent resorting to subjective judgment in assessing its quality.

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[3] G. Taguchi, *The System of Experimental Design: Engineering Methods to Optimize Quality and Minimize Cost* (Kraus, 1987).

2. The tradeoff between providing detailed specifications of service and the cost involved in defining these specifications and inspecting against them.

3. The wide variety of services performed at the same installation and even within a single contract.

4. The great variability among service contracts.

5. The service effort's dependence not only on the required condition of the facility after service, but also on its condition before service, which may vary greatly among similar facilities. This situation is in contrast to production operations, for which inputs to the production process (e.g., raw materials) are well specified and their homogeneity is generally ensured.

In product manufacture, the control of variability using process control techniques and diagnosis helps to improve quality, enhance productivity, and reduce costs. However, concepts that have been widely accepted in production process control cannot be automatically transferred to service processes without adaptation. It would be desirable to adapt these concepts in view of the opportunities offered by using functional variability as a measure of quality, which include:

1. Motivating the contractor to avoid faults rather than correct them when they occur.

2. Providing an incentive to continually improve quality rather than settle with the current level.

Therefore, this report explores the use of variability as a measure of service performance quality and applies it to control the service quality.

Measurement of Quality in a Service Operation

Data collection is by far the greatest expense in any quality control scheme. Therefore, a primary goal is to minimize the sampling effort (i.e., the sample size and frequency) necessary to make meaningful evaluations while maximizing uses for the data obtained.

When inspecting a service operation, an inspector will evaluate several performance indicators before accepting or rejecting a contract. The sampling method followed is considered to be attribute sampling since the final decision on service operation is either acceptance or rejection, and the outcome is based on the number of rejects in the sample. This method is easy to implement.

The other extreme for sampling methods is variable measurement in which quality is measured by the value of one or more characteristics on a continuous scale. This method provides more information than does attribute sampling because it not only reveals whether an item is good or bad, but also how good or bad it is. As a result, a reduced sampling effort will be required to allow for an assessment of quality.

In service operations, it is hard enough to apply the current attribute measurement, let alone a continuous scale. For this reason, variable measurement usually has constituted an ideal to seek rather than a practical method to follow. However, an intermediate step would be to use a score (e.g., an integer from 0 to 5 or from 0 to 10) that depends on the number of performance indicators violated, their significance, and the severity of the violation. The score also may reflect the importance of the service and whether a fault constitutes a threat to life or property. This type of scale is feasible to implement at no great additional cost. However, its application would require development of new techniques for evaluating service quality and is beyond the scope of this report.

Observation Method

In practice, for a variety of reasons, installations can make only attribute measurements and, therefore, the evaluation methods proposed and discussed in this report deal strictly with these techniques. The concept of proven variability is applied and measures of the variability in sample attributes are used.

Types of Faults in Service Processes

A stable process is one for which output behavior exhibits a nontime variance (i.e., its mean/ covariance structure remains constant). If attribute measurements are being observed on a stable maintenance operation, then these observations will follow a statistical distribution (binomial with parameters n and p') where the parameters remain constant over time. This type of behavior, regardless of how well it matches any desired standard, is very significant because it makes the process output inherently predictable--a property which is always of value. Only in a stable process can judgments be made about true process capability.

Chronic and Sporadic Variability

Two distinct types of variability affect the quality of a service operation--chronic and sporadic. Chronic variability deals with the quality of the process when it is in a stable condition, whereas sporadic variability refers to process quality when special causes (or events) occur to decrease or increase the quality from its stable level.

An unstable process is one for which behavior changes, either through changing process parameters or through special causes entering the system. The result may be an increase or decrease in process quality. As an example, consider the Venetian blind cleaning operation again. The contractor may employ one person who, over a given time span, is solely responsible for this service. Given that this person uses the same methods and equipment over time, his or her output quality can be modeled as a stable process (regardless of the actual level of quality this process attains on the average). A special cause may enter the process in a variety of ways. For example, the regular person may be sick one day and a substitute is used; there is a strong chance that the substitute's methods will not be the same as the regular's, and thus, the parameters describing the quality of output from the substitute will differ from those of the regular, or stable, process.

Quality improvement can be affected in two ways: first, removing special causes, if any exist; second, reducing the variability of the process output under stable conditions. In practice, the first step is usually much simpler than the second. It is therefore emphasized that any proposed evaluation method should take into account this goal and thus should be able to separate chronic and sporadic variability.

Faults Within the Process

For this report, a "fault" is defined as any special cause that changes the parameters of the stable process. Thus, a stable process will have no faults, and an unstable one will have faults that occur either randomly or in a pattern over time.

The example given in the previous section describing chronic and random variation can be used again. The Venetian blind cleaning operation is performed by a regular and a substitute person; the regular operator performs at a higher level of quality than the substitute. If the occurrence of the substitute occurs at random intervals over time and for only one time unit per appearance, then this fault pattern is considered to be a random shift (or spike shift) in the process mean, described by its rate and magnitude of occurrence.

If, however, the regular and substitute operator trade responsibilities in some regular manner, say every month, the fault occurrences become patterned (in this case, a step shift in the mean level of the process) because the unstable mean switches between one value and another at regular intervals. Besides this step shift in the mean, other patterns of fault occurrences have also been considered, namely, a linear trend in the mean, a sinusoidal trend in the mean, and a sawtooth (irregular but patterned) trend in the mean. The types of fault will be discussed in more detail in Chapter 3.

Quality Control Approaches

The methods surveyed for sampling and evaluating service quality can be divided into three major approaches--acceptance sampling, hypothesis testing, and control ng. Each approach has potential application for monitoring and improving service quality. In studying methods used at the installations, MIL-STD-105E and the Facilities Engineering Support Agency (FESA)* plans emerged as examples of the acceptance sampling concept. These methods are described along with the theories behind each approach. The Dodge and Romig plans are not considered here because their assumption of rectification (i.e., all defectives found are replaced by good services and reject lots are 100 percent inspected) is not fulfilled.

Acceptance Sampling Approach

A central point in sampling theory is that a sample should be representative of the whole population (in this case, a whole lot). Quality will be measured on a scale of accept or reject and inspection by attributes will be used. In this case, each element of the lot is classified as defective (if it does not meet the requirements) or nondefective. The number of defectives in a sample would then be an indication of output quality as a whole.

Acceptance sampling involves the following parameters:

N = Lot size of process

n = Sample size

c = Number of defects in sample of size n that will deem the lot unsatisfactory (rejectable)

x = Number of defects found in sample

p = Sample fraction defective = x/n

p' = True process fraction defective

α = Producer's risk

β = Consumer's risk

AQL = Acceptable quality level

LTPD = Lot tolerance percent defective.

The service operates on what is referred to as a "lot." In some cases, the lot definition may be very straightforward (number of beds changed in a hospital during 1 day of operation), or it may be rather ambiguous (number of calls for residential maintenance in a period of 1 month). The definition should be chosen so that it corresponds realistically to the service frequency. For example, if beds are changed daily, then the lot size should be the daily total--and not the weekly or monthly total. The true process

* After this study was completed, FESA reorganized and is now the U.S. Army Engineering and Housing Support Center (USAEHSC).

quality is characterized by the parameter p' and an objective measure of this quality is contained in the sample statistic, p.

At a given instance, a simple sampling plan would be:

1. Take a random sample (without replacement) of size n from a lot of size N.

2. Determine the number of defectives (x) in the sample.

3. If $x < c$, accept the lot; otherwise reject it.

The probability that a lot is accepted is a function of N, n, c, p', α, and β. In any sampling scheme, the probability of lot acceptance should be high for satisfactory lots and low for unsatisfactory lots. This "probability of acceptance" is described by the plan's operating characteristic curve as explained further in Chapter 4.

In short, consumer's risk (β) is the chance that poor quality lots will be accepted; producer's risk (α) is the chance that satisfactory lots will be rejected. These risks characterize the two military plans in this category: MIL-STD-105D and FESA sampling plans.

Military Standard 105D. This sampling system is the outgrowth of the Armed Forces and the joint Army/Navy tables. The present system is the third revision of MIL-STD-105A. Its basic aim is to ensure that, on average, the consumer will be using services at the specified acceptable quality level (AQL) or better. It is designed such that, if a producer runs the process at the AQL exactly, a great majority of the lots will be accepted. This probability of acceptance at the AQL runs from about 0.88 for small lots and relatively tight AQLs up to about 0.995 for large lots and/or relatively loose AQLs. If the producer runs the process at p' higher than the AQL, some lots will be accepted but sooner or later the sampling plan will move to "tightened inspection" and a smaller proportion of the lots will be accepted. If the output quality p' returns to an improved level and stays there for a specified period, inspection will return to the norm; if the quality is much better than the specified AQL, the plans will move to "reduced inspection." The sample sizes used for reduced inspection are on the average, 40 percent of the normal one.

Sometimes it is desirable to switch the sampling inspection from normal to tightened or reduced, and vice-versa. The standard includes switching rules to ensure that a poor quality process is examined more stringently and an excellent quality process is examined with reduced sampling effort. The sample size and acceptance/rejection numbers required for normal, tightened, and reduced inspection are given in their corresponding MIL-STD tables.

To switch from normal inspection, the rules are:

1. If the past 10 lots have been accepted and the total number of defectives is less than the limit number of the inspection scheme (given by Table viii of MIL-STD 105D), switch to reduced inspection.

2. If two of the last five lots have been rejected, switch to tightened inspection.

To switch from reduced inspection, the rule is: if a lot is rejected, return to normal inspection; from tightened inspection, the switching rule is: if five consecutive lots have been accepted, return to normal inspection.

The reason for switching from normal to reduced inspection is to test whether the estimated process average computed as the fraction defective in the last 10 samples is significantly smaller than the AQL. The "limit" numbers specified in table viii of MIL-STD-105D are the lower two-sigma limits for the Poison distribution. In previous editions of the MIL-STD tables, an upper three-sigma limit was used as a condition for switching from normal to tightened inspection but was replaced to follow the "two out of five" rule suggested by Dodge[4] because inspectors considered the former rule numerically laborious.

The following steps are taken to obtain a sampling plan:

1. Select the size of the lot, N, to be sampled and inspected.

2. Determine an inspection level from general level ii of MIL-STD-105D.

3. Using values from 1 and 2 above, consult table i of MIL-STD-105D to find the corresponding sample size code letter.

4. Choose single, double, or multiple sampling.

5. Start with normal sampling.

6. Identify the appropriate MIL-STD table on the basis of Steps 4 and 5 above.

7. Specify the desired AQL.

8. In the table identified in step 6, locate the entry at the intersection of the column corresponding to the AQL specified in step 7 and the row corresponding to the code letter determined in step 3. This entry gives the acceptance/rejection numbers with the sample size(s) listed to the left of the block.

FESA Sampling Plans. These plans do not use a mere heuristic relationship to determine sample size as in the case of MIL-STD-105D; rather, they introduce the concept of accuracy. "Accuracy" is defined as the amount that the sample mean can exceed the AQL level before the contractor's performance is judged to be unsatisfactory and deductions are made from the contract price.

The concept of levels of inspections is similar to that in MIL-STD-105D. These levels are defined in terms of a fixed value of accuracy. To summarize:

	Accuracy	Confidence Level
a. Normal inspection	0.10	0.90
b. For tightened inspection	0.05	0.95
c. For reduced inspection	0.15	0.85

It is not clear how to decide which level of inspection to use because switching rules are not stated clearly. Furthermore, assignment of accuracy levels to each inspection appears quite subjective. The decision rule is similar to the one for MIL-STD-105D: given a lot size and a specified AQL, obtain a rejection number and compare it with the number of defectives in the sample.

The arbitrary assignment of accuracy to different inspection levels weakens the usefulness of this method. Indeed, the field work survey suggested that these inspection levels are rarely used, if ever.

Confidence Interval Approach

The confidence interval approach is a popular technique of statistical inference to test if there is statistical evidence that a given set of data comes from a population with parameters, say p.

[4]H. F. Dodge.

A confidence interval is determined by two random functions of the data, the lower control limit (LCL) and upper control limit (UCL), such that with a high probability (e.g., $1 - \alpha$) this interval will cover the parameter to be estimated, i.e., ? $\text{Prob}(LCL < p' < UCL) = 1 - \alpha$.

A confidence interval is a test of the hypothesis that the sample came from a parent population with parameter p'.

Given a sample of size n from a lot of size N, the decision rule used to reject the lot is if the LCL is greater than AQL (see Chapter 4 for the confidence interval formula). When sampling from a finite population without replacement, it can be shown that the distribution of the variable x (= number of defectives in the sample), follows a hypergeometric distribution with parameters N, n, and p'.

"Replacement" refers to the act of replacing samples after each is evaluated. As N increases, the replacement assumption becomes less important and the distribution tends toward the binomial.

It is usually rare to obtain exact confidence intervals for the hypergeometric distribution given a particular level α. The reason is that for discrete random variables, given a particular value α, the corresponding cumulative probabilities generally will not give an integer solution.

Control Chart Approach

The control chart approach is a sophisticated, yet simple, test of hypothesis that takes into account two neglected aspects in other methods: historical information of the process and time order. A control chart is defined by three control lines plotted against time. These three lines are LCL, Center Line (CL), and UCL. These three lines are a function of the historical record of the process under study.

One important difference between this approach and previous approaches is that the control chart approach is not based on the AQL concept but on the average stable behavior of the process. The hypothesis tested is whether the process continues to be stable as compared with historical information of the process under stable conditions.

The inclusion of these two aspects makes control charting a very powerful method. Historical information provides a more reliable reference for comparison than a single sample or an arbitrary value (AQL) and consequently ensures greater confidence in the results. Furthermore, the time sequence allows the theory of runs and nonparametric tests to be used to determine any anomalous or extraneous departures of the data from the assumed model.

The decision-making procedure assumed for this report is:

1. If a sample of size n has a value of p which is beyond the control limits, or

2. If a run of seven consecutive subgroups have values of p above or below the centerline, then--an alarm is signaled.

Process control is an example of a statistical method based on the control chart approach. Because control charting appears to be such an effective tool, process control methods were studied in detail. A brief overview is given below; Chapter 4 gives the details of process model representation/simulation.

Process Control Methodology

One of the primary goals of process control is quality improvement, which is achieved through fault diagnosis and correction. Process control methods partition process variability into common and special (chronic and sporadic) causes. This division of variability, along with the fact that the p-chart is an excellent visual tool for examining patterns that may exist within the evolution of the process quality, is one reason why process control methods are used. Another advantage of process control is that it takes a historical perspective of the process behavior and uses information based only on samples taken from individual lots.

Process control uses a series of fault diagnosis steps to improve quality. First, a process history is formed to assess the true process percent defective average. During establishment of this history, special causes of variability will arise, manifest as points out of control on the p-chart. These special causes should be diagnosed properly and removed from the process.

When all sporadic causes of variability have been removed from the system, the evaluator can truly assess the level of quality produced by the maintenance contractor with respect to the AQL as negotiated in the contract. If this level of quality is not satisfactory, the evaluator must investigate ways of reducing this common cause variability--usually by either reassessing process methods or reevaluating job requirements.

In addition to their usage in fault diagnosis and process improvement, process control methods are recommended for supporting acceptance sampling schemes. These schemes are based on an assumed process average; however, estimates of process average can be meaningless if the process is not stable. Process control methods verify process stability so that estimates of process average become more reliable.

3 PROCESS MODEL REPRESENTATION AND SIMULATION

A general computer simulation program was designed to evaluate the techniques for monitoring the quality of services rendered by maintenance contractors. Requirements for the simulation were that it: (1) realistically model the service contract functions currently being performed at military installations, (2) contain a varied choice of methods for surveillance of the service quality, and (3) be straightforward and easy to run. The computer program was written in FORTRAN.

The package contained three modules: CREATE generated a database for a typical service contract process and also allowed modification of this base; MAINT1 simulated the observation and evaluation elements of a problem when faults were generated randomly; and MAINT2 simulated the observation and evaluation elements of the problem when faults were generated in some pattern.

Development of the simulation program depended in part on forming an accurate representation of the service process. The next section describes how the service operation was modeled for application to military installations.

Modeling the Service Process

Transfer Function Representation

A transfer function is a generic model of a process that relates its outputs to its inputs and process variables and thus depicts how input quality is transformed to output quality. The only input into the transfer function is the initial quality of the system to be serviced. This quality represents the level of service required to bring the process output up to required standards; for instance, if input quality is very high (e.g., the floor to be cleaned is not dirty), then output quality will necessarily be high as well, regardless of the methods or materials used by the servicer. The transfer function variables, which are to a large extent controllable, are the equipment, personnel, and methods used to perform the service operation. Other nuisance variables may affect the output quality (variables that may not be controllable such as environmental factors).

Types of Processes Represented

There are two reasons to divide the service processes into categories. First, this classification provides some understanding of the wide range of operations performed and monitored at any given installation. Second, this classification may be useful later in determining the sampling and evaluation scheme (e.g., choice of attribute or variables measurement and proper sample size). For instance, more important jobs probably should be sampled more frequently than less significant ones and possibly with a larger sample size.

Five general categories of contract service processes have been identified and are representative of all services performed at a particular installation:

1. Frequent and routine--

   - Glass cleaning
   - Refuse disposal
   - Lawn maintenance.

2. Infrequent but routine--

   - Air-conditioning equipment maintenance
   - Pest control
   - Roofing.

3. System operation--

   - Water treatment
   - Records/files maintenance
   - Food service.

4. As needed--

   - Snow and ice removal
   - Taxi service
   - Urgent service calls
   - Nonurgent service calls.

5. Operation and Maintenance--

   - Contracts
   - Computer maintenance
   - Telecommunications.

These classifications were used in the simulation experiment as described in detail in Chapter 5.

Process Representation for Simulation

In attempting to control a process, the first decision must be to choose the type of observations that will be made. Given the transfer function representation described above, the process variables can be monitored in real time and control their effect on output quality; or, output quality can be monitored and an attempt made to reduce variation within the process variables. Given the installations' manpower constraints, the only alternative is to monitor the maintenance service output quality after the fact.

Although the data base creation program has an inherent ability to create processes for which observations are attribute or variable, the simulation programs deal strictly with attribute data classified as acceptable or unacceptable.

Also within the structure of the transfer function is how certain variables within the process affect the output quality. For instance, suppose the output quality in question was the number of air-conditioning units that had filters replaced properly and on time. Several process variables such as the training of the server or service person, the quality of scheduling performed by the contractor, the filters' prior condition, and the location of the air-conditioner unit could directly affect whether a particular unit is serviced properly. The simulator allows these types of transfer function variables to be modeled realistically so that the effect certain variables have on the output quality of the process can be seen.

The simulator works on the premise of transfer function variable states; these states determine how the process output is generated. Each transfer function variable is allowed to have two states: first is the "normal" level which will not change the level of any process parameter (i.e., the process remains stable and is operating only under a system of chronic variation); the second is the "faulted" state which may or may not change the value of the process parameters, signifying a special cause wherein the process operates under sporadic variation. In the CREATE module, the user is asked about the value of the transfer function parameters while the variables are in a faulted state. These values can either be estimated from real life data analysis or manipulated experimentally.

Simulating the Service Process

A brief overview of the three modules within the simulator is provided here to show how the system incorporates the statistical concepts under study. Chapter 5 on experimental testing contains more details on the simulator's operation and output.

Creating Processes Within the Database

The program module CREATE was developed specifically for creating and modifying a database structure for the processes. The size of the database created is unlimited; however, it may be easier to create a series of small databases pertaining to specific problems rather than having one huge database. Because all the programs assume that the database being used is named DATA.BSE, the user can simply name the various databases differently for storage and then rename them to DATA.BSE upon use.

The user has the option to create, modify, or delete processes within the database; the modify and delete options are self-explanatory; each process currently residing in the database is shown and the user is asked to specify which process to modify or delete.

To create a new process within the database, the user must supply information to a series of character strings. The character strings are open-ended, meaning they can be left blank or filled with any expression desired. The analysis programs use these strings to facilitate process selection and to identify the process in the output. The strings describe the process and the transfer function; give the name of the observable quality characteristic; give the probability of each transfer function's being in the Faulted State; define the lot; and list any comments.

To begin, the user enters a unique name to identify the process. Next, the transfer function must be described mathematically. To do this, the names of the transfer function variables and their two corresponding states must be input. The number of transfer variables allowed is eight; all blanks are ignored during simulation. At least one transfer function variable must be present. Next, the distribution of the observable output quality characteristic is input; the user chooses between binomial and hypergeometric. MAINT1 and MAINT2 work only with processes for which distributions of characterization are binomial or hypergeometric.

The next inputs deal with how faults are generated within the process. For each transfer function variable, the probability that the variable is in its second (faulted) state must be input. The simulator also needs to know the distribution parameter(s) when that variable is in its second state. If the value given is equal to the original parameters, no fault is generated; if the value is different, a fault of given magnitude is generated whenever that variable is in its second state. The final numerical value that must be input is the lot size.

In modifying a process within the database, all inputs can be changed. The method for doing so is clear from information within the program.

The Simulation of Random Faults Through MAINT1

As mentioned earlier, the MAINT1 program simulates the observation and evaluation elements of the QC window, providing several techniques for generating evaluation data. The generated output is of acceptable/unacceptable type data and is derived from the underlying distribution contained within the database definition of the simulated process. The distribution parameters depend on the state of predefined transfer function variables.

At each time unit, the state of each transfer function variable is determined according to the probabilities input within CREATE. If all transfer function variables are in their first state, the parameter used is the one corresponding to the stable process; if any one of the transfer function variables is in its second state, then p' is chosen as the maximum value of all possible faulted p's. For instance, suppose proper filter replacement is being monitored and the conditions are:

Transfer function variables: training of servicer
location of filter

Possible states of training: experienced, rookie

Possible states of location: accessible, difficult to access

Probability of servicer being rookie = 0.30

Probability of location being difficult to access = 0.10

Value of p' when servicer is experienced, location accessible = 0.05

Value of p' when servicer is rookie, location accessible = 0.10

Value of p' when location is difficult to access = 0.40

The states are generated according to the probabilities stated above, and the predescribed rules below are used to assign the value of p':

Servicer experienced, location accessible > p' = 0.05

Servicer rookie, location accessible > p' = 0.10

Servicer experienced, location difficult to access > p' = 0.40

Servicer rookie, location difficult to access > p' = 0.40

The process output generated is described under **Interpreting Simulation Results** below.

Running the MAINT1 Program

At the start of the MAINT1 program, the user must indicate whether the process to be simulated should be selected from the database or created online. If the process is selected from the database, each process will be shown on the terminal screen in order of creation and the user indicates which one is to be chosen.

Next, the simulation length, or number of simulated subgroups, is chosen. This can be any number up to 512, but it is recommended that the user select some number between 100 and 250. This length will remain constant over all QC windows chosen and trials run.

The user must select the technique to be used within the QC window. The basic choices are: (1) a confidence interval based on a single subgroup, (2) a confidence interval based on several subgroups, (3) a p-chart, and (4) acceptance sampling. Within each choice, there are several options on how to set up the analysis. Inputs common to all four are the sample size (under normal inspection for acceptance sampling) and the process AQL. As mentioned in Chapter 2, all methods except the p-chart make their evaluations based on a comparison with the AQL; the p-chart evaluates stability, regardless of the AQL's magnitude.

When a confidence interval using a single subgroup is chosen, the user must state the level of confidence (1, 2, or 3 σ) and decide whether to base it on the binomial or hypergeometric distribution. There is also the option of either basing the estimate of σ on the same single subgroup or using historical information. If the second option is chosen, the user must input the number of consecutive subgroups to use in estimating σ. When a confidence interval using $\bar{p}$ is chosen, this window of subgroups is also used to estimate $\bar{p}$, the center of the confidence interval. Another option is offered when several subgroups are used for estimating either p or σ. When selection of the subgroups is indiscriminant, a moving window of a constant number of consecutive subgroups is used; when subgroup selection is discriminant, a moving window of varying size is used, disregarding all subgroups that are out of control on a corresponding p-chart (thus using subgroups from a single population for the estimation procedure).

When the p-chart option is chosen, the user must first decide how many subgroups to use in estimating the centerline p and, thus the corresponding control limits. In generating the process output, the simulator assumes this set of subgroups comes from a stable population. For instance, if 10 subgroups are to be used for the centerline estimate, the first 10 subgroups generated in the simulation run will automatically come from the process parameter corresponding to a stable condition (i.e., the process is frozen in a stable state for that many subgroups).

There is also an option for switching the diagnostic procedure on and off. Because the p-chart is a diagnostic tool, it is logical to assume that the chart's prolonged use eventually will identify special causes and remove them from the process. When the diagnostic program is running, each fault caught on the p-chart is identified and removed, thus making it impossible for that particular transfer function variable to reach its second state (i.e., making it impossible for that variable to create a faulted condition).

When acceptance sampling is chosen, the user must determine the appropriate plans to be used by inputting the reject number and deciding whether to enable switching rules. The switching rules are the same as those used in MIL-STD-105D and, if they are chosen, the user must input the sample sizes for reduced and tightened inspection, the reject numbers for reduced and tightened inspection, and the acceptance number for reduced inspection.

Running the MAINT2 Program

The MAINT1 program simulates processes for which faults are generated randomly; the effect of each fault is present only for the particular time unit in which the fault occurs. In contrast. MAINT2 simulates processes for which faults are generated in a specific pattern, and these faults can affect the process output for several time units after they occur. The patterns represented are: (1) a step shift in the process mean, (2) a linear shift in the process mean, (3) a sinusoidal trend in the process mean, and (4) a sawtooth (irregular but patterned) trend in the process mean.

To understand how such a pattern could arise, refer to the example of changing air-conditioner filters in Chapter 2. Suppose the maintenance contractor uses two distinct crews for this filter replacement, each working on alternate weeks. It is probable that the crew skill levels will differ, leading to a shift in the process mean each time the more "unskilled" crew works. Thus, the fault represented is a step shift in the process mean, and its magnitude is determined by the corresponding skill level of the crew assigned to the task.

The user is prompted to identify which fault pattern is to be simulated. Common to all the patterns, the user must specify how many subgroups are present within the two stages of the pattern (the stage where p' is at its stable level and the stage where p' changes according to the pattern chosen) and the maximum value of p' during this patterned stage. It should be noted that, except for the step shift, all other patterns work under the premise that the first subgroup in the pattern is at the original, stable value of p'. For instance, if a linear trend that lasts for three subgroups raises the values of p' from 0.05 to 0.15, then the value of p' for the three subgroups in the "faulted" cycle are 0.05, 0.10, and 0.15. The rest of the prompts corresponding to QC window selection are the same as in MAINT1.

Interpreting Simulation Results

The simulation output contains the information necessary to evaluate and compare advantages and disadvantages of each evaluation technique. This output is provided at the end of each trial run and the results are averaged. The user also can request interim output by subgroup to show the evaluation results and transfer function states at each point in time, if desired.

The first output is the number of faults. For MAINT1 (except when p-chart is chosen), a fault is tallied each time the value of p' is above the AQL. In MAINT2, a fault is tallied for each subgroup where p' is not equal to its original, stable value. This rule is also used to talley the number of faults for MAINT1 and MAINT2 when the p-chart option is chosen.

The next output is the number of alarms. An alarm is counted each time the particular analysis method is triggered. Alarms are defined as true or false. A false alarm is tallied each time the analysis method is triggered but a fault is not present. This situation corresponds to the producer's risk. Also output is the number of subgroups where p' was above the AQL. For MAINT1 (except p-chart), this number is the same as the number of faults; for the other conditions, this number may differ significantly from the number of faults. Thus, the number of true alarms is the number of alarms minus the number of false alarms, and the number of faults missed is the number of faults minus the number of true alarms.

Additional information is provided on the total sampling effort over the complete simulation run. If switching rules are used within acceptance sampling, the number of lots inspected on tightened, normal, and reduced sampling plans is included.

The most useful number for comparative analysis of methods is the ratio of true detections to faults. This number basically normalizes all other effects that may make results difficult to compare (e.g., the rate of fault occurrence, simulation length) and allows a direct comparison of the analytical techniques over a variety of simulation test designs. This ratio and the relative occurrence of false alarms provide statistics for comparative analysis.

A final statistic is provided to aid in assessing a penalty, although by no means should these results be interpreted solely to make a decision on which penalization scheme to employ, if any. For all analysis methods, a penalty is assessed each time an alarm occurs, false or true. Two methods are used to estimate the percent penalized. The percent penalized by method one is given by:

Confidence interval - value at the lower end of the interval

p-Chart - value of $\bar{p}$ (the centerline)

Acceptance sampling - value of sample result (percent defective).

The percent penalized by method two is the same as for method one for the p-chart; for the acceptance sampling and confidence interval approaches, the AQL is subtracted from the percent in method one.

4 THEORETICAL EVALUATION OF QUALITY ASSESSMENT METHODS

Overview

Chapter 2 discussed three basic methods of assessing the quality of the service function--acceptance sampling, confidence intervals (hypothesis testing), and control charting (process control). This chapter discusses these methods in more detail and compares them theoretically.

The basic premise is that installations contract for services for which quality is monitored upon completion and delivery of the service. As discussed in Chapter 2, the quality characteristic being monitored will be measured as an attribute: the service will be compared with the standard to determine if it is acceptable or unacceptable. The sensitivity and size of the sampling effort as well as the expected results greatly depend on the analysis method chosen.

Two different aspects of service quality were analyzed in this study--stability and capability. "Stability" refers to how much of the process variation is due strictly to common causes (system or inherent) as opposed to sporadic variation due to special, assignable causes. Only the process control approach can monitor process stability.

The second aspect, capability or conformance, estimates how well the process quality meets the standard. In this case, the standard is the AQL, which is the percent defective output that the service is permitted before the entire job is considered unacceptable. The AQL often is stated directly within the service contract. The lower the AQL, the more careful the contractor must be with quality (and also the more effort required for a sampling effort, as will be shown later). Both acceptance sampling and confidence interval approaches can analyze process conformance.

For the theoretical discussion, the methods are described in terms of their operating characteristics (OC) curves. The OC curve of a given method is a function that relates the probability of accepting the sampled lot (P_a) to its true percent defective and depends on the particular sampling parameters chosen for that test.

An ideal test is one that has an OC curve with $P_a = 1.0$ at values of p' below the AQL (i.e., accept all lots better than the AQL), and $P_a = 0$ at values of p' above the AQL (i.e., reject all lots worse than the AQL). This OC curve can be obtained only with 100 percent inspection of the entire lot. Since 100 percent inspection is unrealistic, the OC curves of various plans attempt to approximate this shape while still adhering to other constraints such as cost.

An important consideration underlying this analysis is the probability distribution of the number of defectives. Two common distributions in this application area are the binomial and hypergeometric types. The binomial distribution applies when the lot size is infinite; the hypergeometric type applies when a finite lot size is assumed and replacement is not used. In general, sampling plans will appear more powerful (for both producer and consumer) if the hypergeometric distribution is assumed. In the context of the methods being analyzed, the lot is finite and replacement is not made; thus, a hypergeometric distribution will be used.

Acceptance Sampling

In general, acceptance sampling plans can be determined by two points on their OC curve corresponding to their producer (α) and consumer (β) risks versus some prespecified values of p', the true process percent defective. Producer's risk is the chance that a satisfactory lot will be rejected; consumer's risk is the chance that an unsatisfactory lot will be accepted. A variety of sampling plans usually can be designed, all with varying sample sizes that virtually pass through these two points on the OC curve. Because of the discreetness of the sample size and reject number, a sampling plan giving exactly equal protection often is impossible.

The MIL-STD-105D plans are based on producer protection, especially when level I or II inspection is used. This means that, over the long run, these plans will give more protection to the contractor than to the installation. A specific producer's risk is not inherent within the plans--consumer protection is achieved by using tightened inspection. In contrast, the Dodge-Romig plans are based on the assumption of 100 percent rectification where an Acceptable Outgoing Quality Level (AOQL) is chosen; these plans are largely designed to ensure consumer protection. Since rectification (i.e., inspection) is cost-ineffective and expends large amounts of manpower (and thus is inappropriate for installations), rectification plans will be ignored in the analysis.

The MIL-STD-105D tables are designed such that a plan can be chosen by specifying the AQL, lot size, and level of inspection. Although level III inspection will give better consumer protection than level I or II, these plans are basically designed in favor of the producer. They become less stringent as the lot size increases because of the importance of not rejecting an entire lot incorrectly. Switching rules take a somewhat historical perspective of the process into account by tightening evaluation if poor quality is exhibited and by reducing sampling effort if excellent quality is found. Switching rules makes the plans more difficult to use, but they must be included to ensure that the protection originally designed into the plans is achieved.

Denoting the following quantities:

P_a = Probability of accepting a lot where the process mean is p'

P_a^n = Probability of accepting a lot where the process mean is p', under normal inspection

P_a^t = Probability of accepting a lot where the process mean is p, under tightened inspection

Prob(normal) = Probability that the inspection plan is at the normal level

Prob(tightened) = Probability that the inspection plan is at the tightened level.

From Hald[5], it can be shown that:

$$P_a = P_a^n \bullet \text{Prob(normal)} + P_a^t \bullet \text{Prob(tightened)} \qquad \text{[Eq 1]}$$

$$\text{Prob(normal)} = \frac{(2-P_a^{n\,4})(1-P_a^n)^{-1}(1-P_a^{n\,4})^{-1}}{(2-P_a^{n\,4})(1-P_a^n)^{-1}(1-P_a^{n\,4})^{-1}+(1-P_a^{t\,5})(1-P_a^t)^{-1}\,P_a^{t-5}} \qquad \text{[Eq 2]}$$

[5]A. Hald, *Statistical Theory of Sampling Inspection by Attributes* (Academic Press, 1981).

$$\text{Prob(tightened)} = \frac{(1-P_a^{t\,5})(1-P_a^{t})^{-1}\,P_a^{t-5}}{(2-P_a^{n\,4})(1-P_a^{n})^{-1}(1-P_a^{n\,4})^{-1}+(1-P_a^{t\,5})(1-P_a^{t})^{-1}P_a^{t\,5}} \qquad \text{[Eq 3]}$$

The quantities P_a^n and P_a^t are calculated from the cumulative binomial distribution function. Table 1 provides a numerical example. A process is chosen for which p' varies and the AQL is 0.01. The results show that the switching rule scheme gives almost equal protection (compared with a scheme that uses no switching rules) at or below the AQL and, at values of p' above the AQL, the OC curve becomes much more tightened or discriminatory.

The switching rules have a drawback in that, for a stable process operating near the AQL, the plans will switch between normal, tightened, and reduced inspections much too often. This happens because the switching rules were designed for ease of use and not out of strict statistical requirements. More realistic switching is obtained by using the original, but more complicated, MIL-STD-105A plans.

Sample sizes in normal inspections are, on average, 10 percent of the lot size. This figure is relatively small; better protection for the consumer is achieved through larger sample sizes.

The basic theoretical conclusion drawn from an analysis of MIL-STD-105D plans is that they are simple to use, but there is a price for this simplicity. The plans offer poor protection for the consumer, and this protection worsens with increasing lot size. Switching rules can provide better protection, but often the rules lead to unnecessary switching. The greatest drawbacks of the plans are that (1) they do not maximize use of the data obtained from the sampling effort because they employ data history only minimally for analysis and (2) they do not lead to results that can be interpreted properly because they do not distinguish between common and special cause variability.

The FESA sampling plans give better protection to both consumer and producer than do the MIL-STD plans when sampling on normal inspection and when lot sizes are large because they use larger sample sizes. When lot sizes are small, FESA plans use smaller sample sizes and therefore offer less protection. The switching rules used are rather ambiguous; thus, it is unclear how they would affect the plan's performances. It is evident, however, that the plans, when in the reduced inspection mode, largely ignore consumer protection; for instance, at an AQL value of 0.10 and a lot size of 200, it is possible for lots with a p' of 0.363 to pass reduced inspection. Accordingly, these plans were not studied further.

Confidence Intervals

The basic function of a confidence interval is to perform a test of hypothesis. In the context of service quality control, the hypothesis will be whether the contractor's service has less percent defective than the specified AQL. In this study, a conservative (defensible) approach is adopted that considers the service substandard if the lower bound of the formed confidence interval (rather than the mean) is above the AQL. It is thus possible to assert with high confidence (95 or 99.9 percent for two or three confidence limits) that the contractor's work did not meet the AQL standard.

Table 1
Comparison of Acceptance Sampling With and Without Switching Rules (AQL = 0.01)

p'	$P_a^n(p')$	Prob(tightened)	$P_a^t(p')$	$P_a(p')$
0.0066	0.99	0.002	0.945	0.98991
0.0109	0.95	0.061	0.865	0.94482
0.0140	0.90	0.228	0.775	0.8715
0.023	0.75	0.781	0.575	0.6134
0.0294	0.50	0.993	0.380	0.3014
0.0409	0.25	1.0	0.120	0.120
0.0535	0.10	1.0	0.045	0.045
0.0620	0.05	1.0	0.020	0.02
0.0804	0.01	1.0	0.003	0.003

A confidence interval can be used to test this hypothesis by using data from either a single subgroup (sampled lot) or several consecutive subgroups. Since both approaches are feasible, both were analyzed. A 99.97 percent confidence interval for the process mean p' is given by:[6]

$$p \pm 3\alpha\, p = p \pm 3 \left[\frac{p\,(1 - p)}{n \cdot k} \left(1 - \frac{n}{N}\right) \right]^{1/2} \qquad \text{[Eq 4]}$$

where k = Number of consecutive subgroups used to estimate $\bar{p}$, the process average
n = Sample size
N = Lot size.

Whether the interval is based on one or more subgroups is significant. While using only one subgroup may seem to maximize "sensitivity" to changes, it decreases overall test performance because the length of the confidence interval increases as k goes toward one, and the shortest interval possible is desired. If more than one subgroup is used to estimate the confidence interval, it should be ensured that these subgroups come from a stable system of common cause variation; this step can be done through using control charts.

Figure 1 shows the OC curves of confidence interval tests as a function of the AQL, k, and N. The two curves depicted show the results for sample sizes of 20 and 50. The first conclusion is that the test sensitivity greatly improves as k increases; the single subgroup plan is very weak for detecting poor quality. Also note that, as the fraction of units sampled in a lot (n/N) is increased, the plans perform better. With respect to this fraction sampled, an increase in the number of samples is more significant than a decrease in lot size. The tests also seem to perform better with a higher AQL.

Overall, the optimal value of k is between 5 and 10. The k value chosen should be no larger than 10 because the interval will start to become too smooth, at which point a large lag will occur between a genuine shift in the process mean and the increase in estimated p' value.

[6]E. L. Grant and R.S. Leavenworth, *Statistical Quality Control* (McGraw-Hill, 1980).

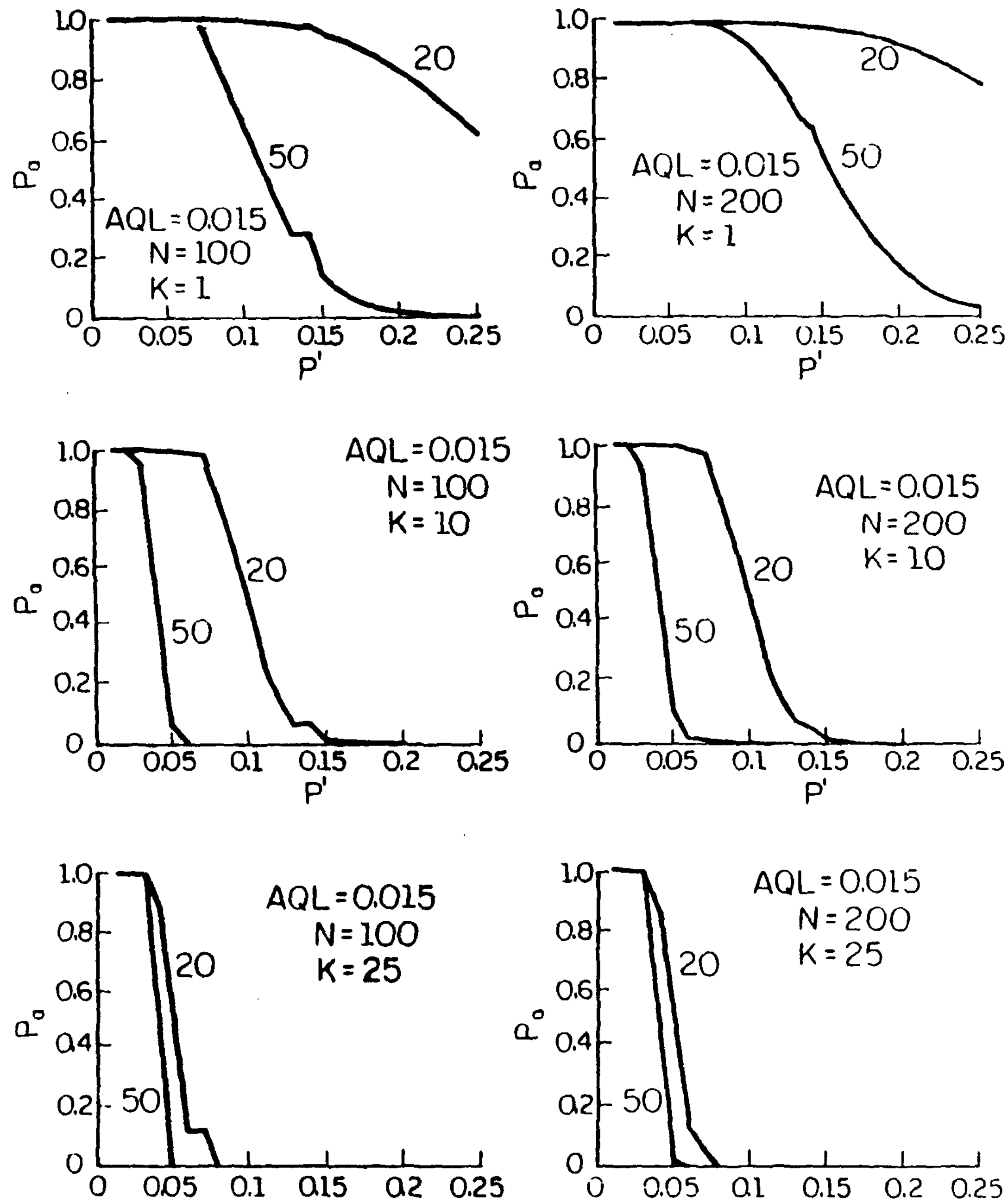

Figure 1. OC curves for confidence interval approach.

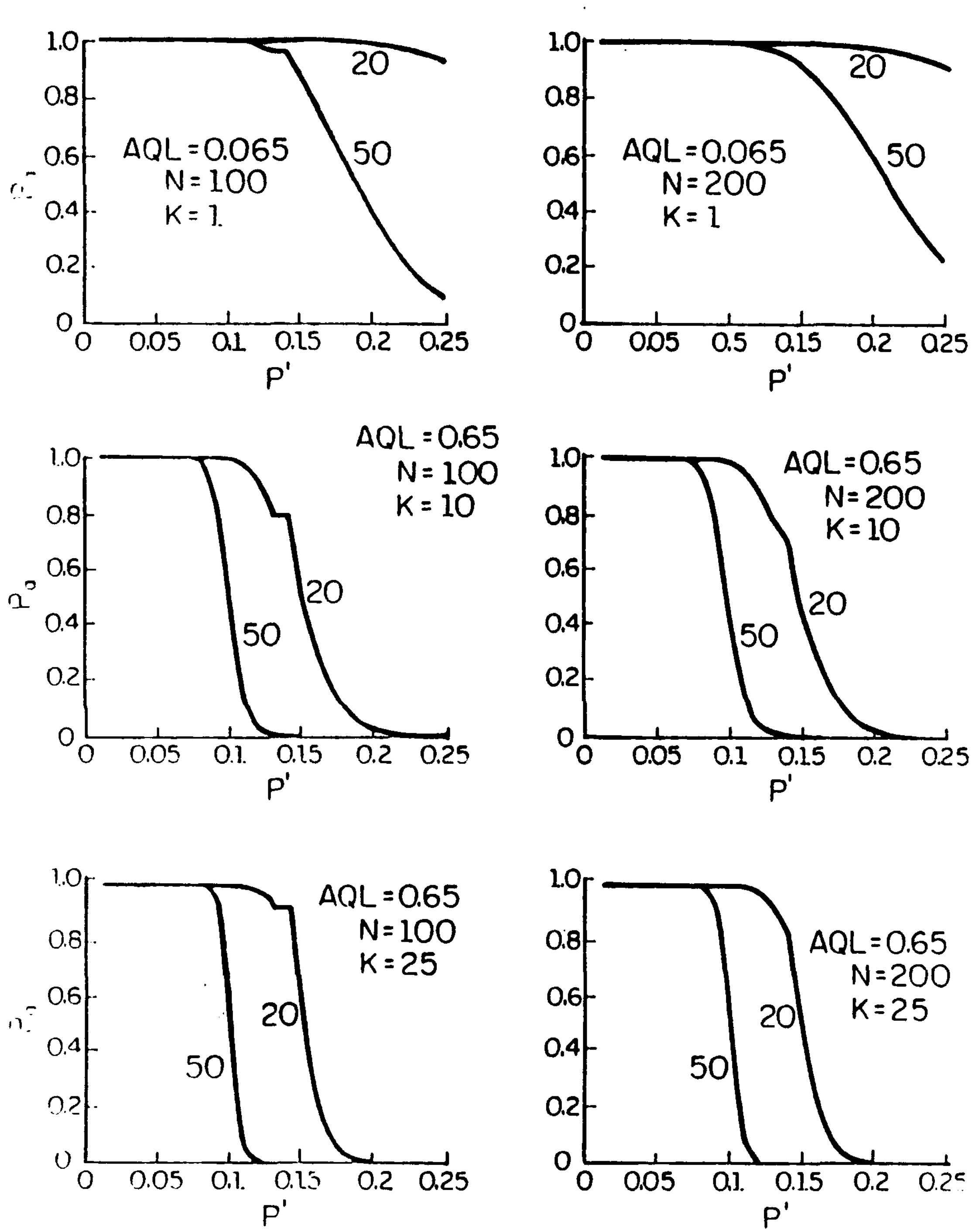

Figure 1. (Cont'd).

Comparison of Acceptance Sampling and Confidence Intervals

Both the MIL-STD-105D acceptance sampling plans and the predescribed hypergeometric confidence intervals are meant for direct comparison of the process average p' with the AQL standard; hence, their OC curves can be compared.

For the analysis, a process with lot size 2000 was chosen, corresponding to MIL-STD-105D sample size code K. The sample size was 125 and the AQL was set at either 0.01 or 0.065. For the confidence interval approach, k was set at 1, 10, and 25. Table 2 and Figures 2 and 3 show the results. Values of p' are shown in each column of the table, corresponding to the particular probability of acceptance given in column 1.

To interpret Table 2, remember that the probability of acceptance (P_a) should lessen as quality worsens away from the AQL. Similarly, the probability of acceptance should increase as quality improves away from the AQL.

At an AQL of 0.01, the OC curve of a confidence interval test with k = 1 is very loose. When k is increased to 10, though, the acceptance sampling and confidence interval tests are essentially equal for values of p' up to 0.02. The confidence interval approach outperforms acceptance sampling at higher values of p'. When k is increased to 25, there is no significant increase in sensitivity over the plan with k = 10. Note that, in the confidence interval approach, the lot is rejected, with p' = 0.0275 for 90 percent of the time; acceptance sampling rejects the same lot only 50 percent of the time.

At an AQL of 0.065, a confidence interval approach performs much better than acceptance sampling. Even the plan using a single subgroup is comparable. With a lot that has a process mean of 0.09, a confidence interval approach (with k = 25) will reject the lot 99 percent of the time whereas acceptance sampling will reject the same lot about 15 percent of the time.

When switching rules are used (plan B in Table 2), there is a general improvement in sensitivity, but the confidence interval approach still performs better than this scheme.

This analysis shows that the confidence interval approach outperforms MIL-STD-105D, and this dominance increases as the AQL becomes higher. Since this superior performance is true over all values of p', confidence intervals are better than acceptance sampling from both the consumer and producer perspective.

Control Charting

The p-chart, with constant control limits, was used to assess process stability. The power of the control chart analysis depends only on the sample size chosen. It was assumed that enough subgroups have been originally collected to estimate the true process average exactly; a collection of approximately 20 subgroups to form control limits should validate this assumption. The test's OC curve was determined by assuming that only points beyond the control limits can signal an alarm (although in practice, a long run above or below the centerline also may indicate a fault). The purpose of the control chart is to distinguish between special and common cause variability, making no external reference to the AQL. It is important to remember that process stability must be established before process capability can be assessed, and only control charting can achieve this end.

Table 2

Comparison of MIL-STD-105D Acceptance Sampling and Hypergeometric Confidence Interval Approaches

p' When AQL = 0.010*

P (Accept)	**Plan A****	**Plan B**	**Plan C**	**Plan D**	**Plan E**
0.990	0.0066	0.0065	0.0400	0.0150	0.0180
0.950	0.0109	0.0040	0.0510	0.0172	0.0195
0.900	0.0140	0.0128	0.0580	0.0185	0.0205
0.750	0.0203	0.0168	0.0695	0.0210	0.0220
0.500	0.0294	0.0248	0.0850	0.0235	0.0230
0.250	0.0409	0.0327	0.1020	0.0265	0.0255
0.100	0.0535	0.0463	0.1190	0.0295	0.0275
0.050	0.0620	0.0527	0.1300	0.0310	0.0285
0.010	0.0804	0.728	0.1520	0.0310	0.0305

p' When AQL = 0.065*

$\bar{P}$ (Accept)	**Plan A**	**Plan B**	**Plan B**	**Plan C**	**Plan D**
0.990	0.0598	0.0599	0.1000	0.0780	0.0692
0.950	0.0740	0.0721	0.1170	0.0830	0.0722
0.900	0.0824	0.0785	0.1265	0.0855	0.0740
0.750	0.0979	0.0881	0.1440	0.0902	0.0765
0.500	0.1170	0.1023	0.1642	0.0955	0.0798
0.250	0.1390	0.1238	0.1872	0.1012	0.0830
0.100	0.1610	0.1418	0.2085	0.1062	0.0860
0.050	0.1750	0.1555	0.2220	0.1095	0.0878
0.010	0.2040	0.1750	0.2480	0.1155	0.0910

*Values of p' needed to give the corresponding P(accept) on the OC curve.
**Plan A: MIL-STD 105D, sample size code k, n = 125; plan B: plan A with switching rules; plan C: hypergeometric confidence interval, N = 2000, n = 125, 1 subgroup, a = 0.0026; plan D: hypergeometric confidence interval, N = 2000, n = 125, 10 past subgroups, = 0.0026; plan E: hypergeometric confidence interval, N = 2000, n = 125, 25 past subgroups, a = 0.0026.

The control limits of the chart, given the estimated p, are:[7]

$$\bar{p} \pm 3\sigma_{\bar{p}} = \bar{p} \pm 3[\bar{p}\ (1 - \bar{p}\ )/n]^{1/2} \qquad \text{[Eq 5]}$$

Figure 4 shows curves for various p-chart plans. A lot size of 200 was assumed (lot size is insignificant in p-charts) and p' was varied from 0.01 to 0.25; when the probability of accepting the lot with a given p' is low, this means the p-chart will detect with great probability a shift in the mean of this magnitude. For instance, when p' is 0.10, the p-chart is expected to detect shifts in magnitudes of 0.22 and larger with great assurance (when a sample size of 60 or greater is used).

The chart monitors stability; hence, it inherently has a low producer's risk. In the long run, the control chart method will pay great dividends because it will lead to results that can be interpreted and give a true estimate of the percent defective, which can later be used within a confidence interval estimation to assess process capability.

The sensitivity (power) of the chart increases as $\sigma \bar{p}$ decreases. Note that $\sigma \bar{p}$ decreases linearly with an increase in the square root of n.

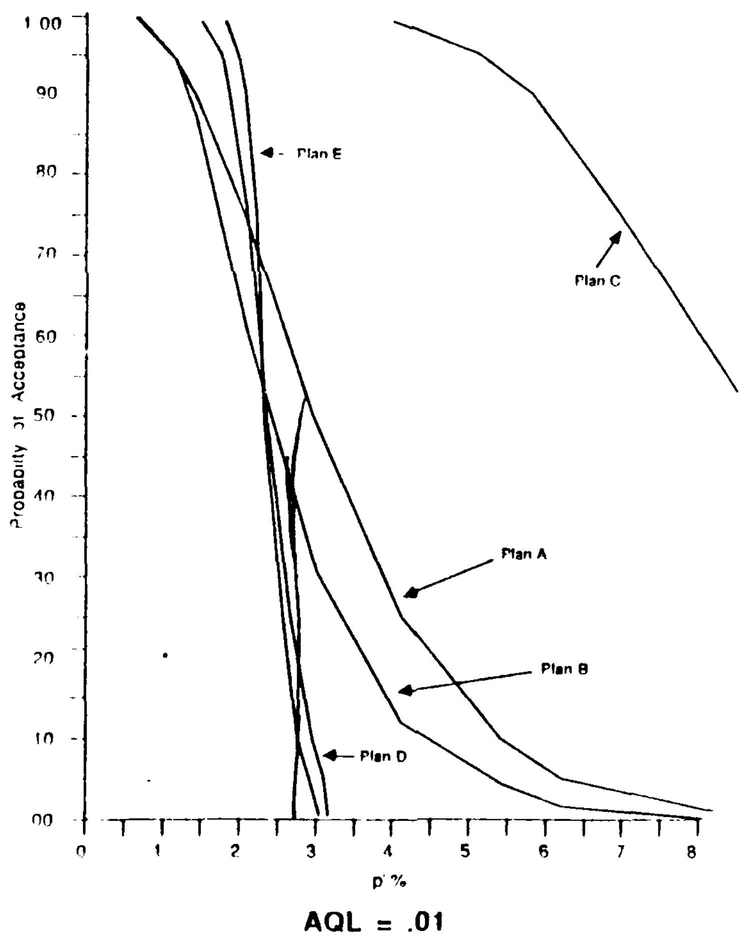

Figure 2. OC curves for the five plans in Table 1 for AQL = 0.01.

[7] E. L. Grant and R. S. Leavenworth.

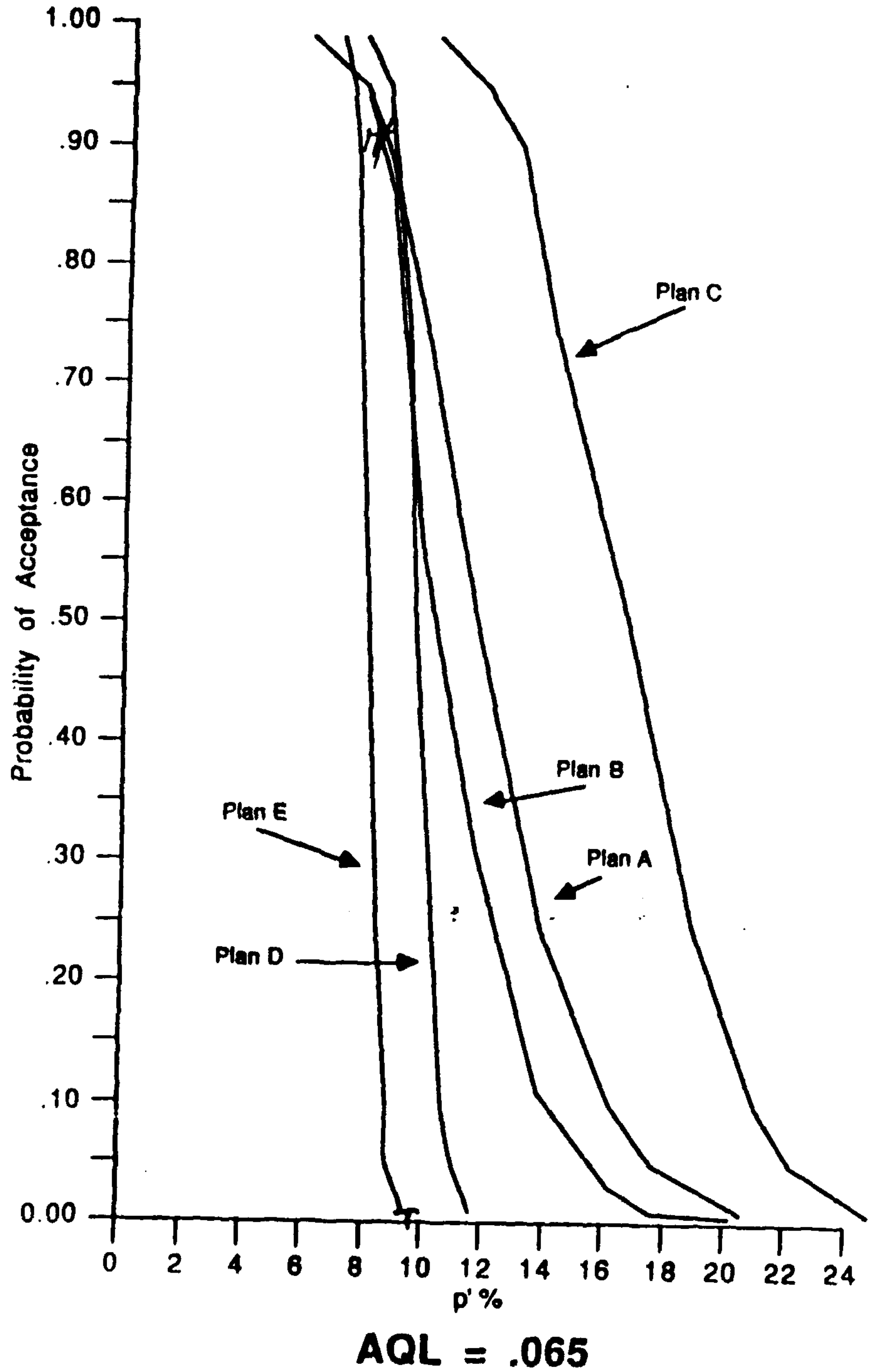

Figure 3. OC curves for the five plans in Table 1 for AQL = 0.065.

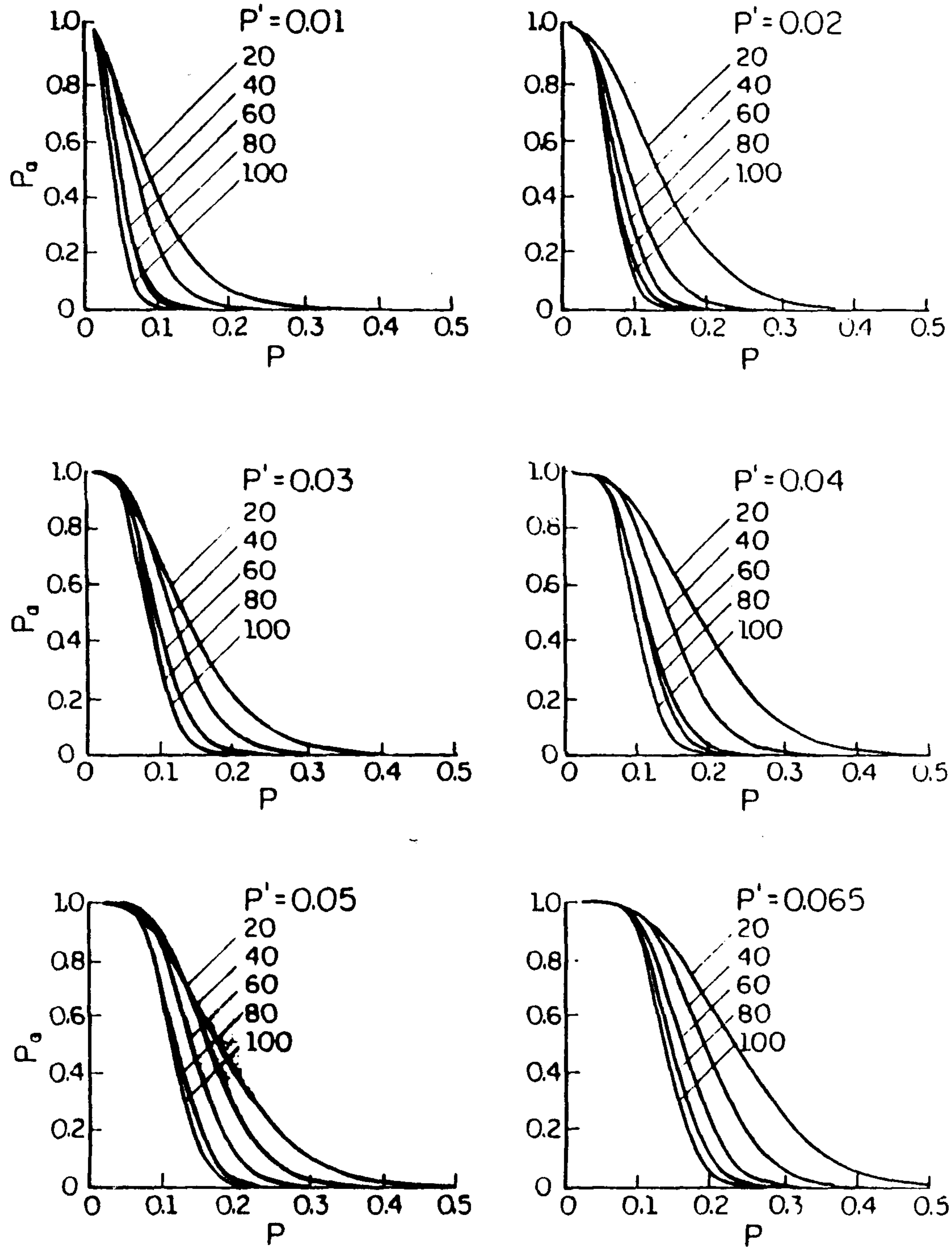

Figure 4. OC curves for the p-chart approach.

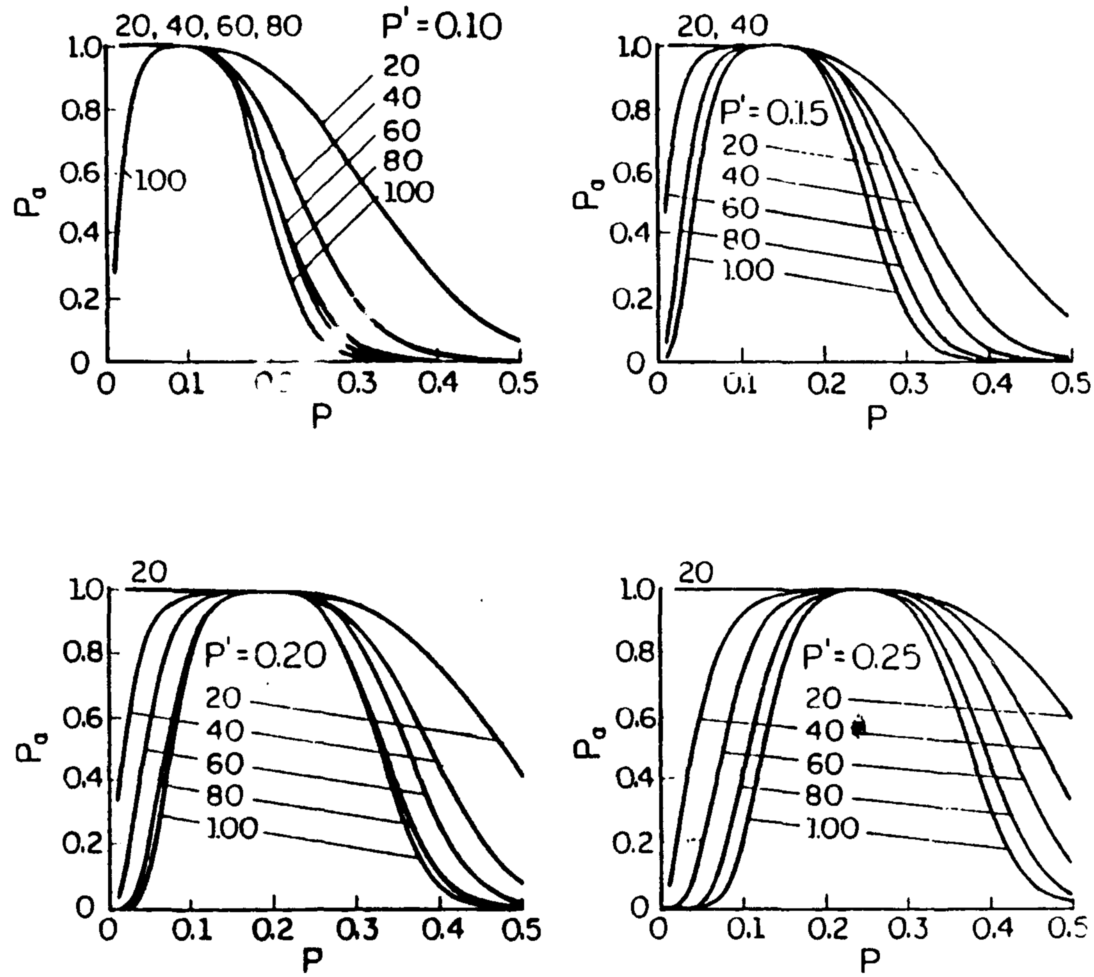

Figure 4 (Cont'd).

5 EXPERIMENTAL EVALUATION OF QUALITY CONTROL METHODS

Experimental Design

A series of simulation experiments was designed to examine performance of the different quality control methods over the range of possible maintenance processes. The steps involved in this experiment were: (1) classifying and selecting representative processes, (2) selecting the relevant parameters, (3) setting parameter values, and (4) choosing process responses to provide the criteria for comparing the different QC methods.

Classification of Processes

Processes were classified to obtain a representative cross section and to establish a basis for the definition of data requirements. Maintenance process data were obtained using documents from Redstone Arsenal, Huntsville, AL, and Fort Hood, TX. The processes were first grouped into the following 12 functional areas:

- Custodial
- Water Systems
- Maintenance and Repair (M&R)--Heating/Cooling
- M&R--Electrical
- Trash Removal
- Pest Control
- Grounds Maintenance
- Roads Maintenance
- Clerical
- Facilities (Buildings and Structures)
- Plumbing
- Service Calls.

Representatives were chosen from these functional areas. Then, based on criteria such as frequency of job performance, skill level required to perform a job, and the importance of a job to the facility, five categories were established as described in Chapter 3: (1) Frequent and Routine Repair; (2) Infrequent but Routine Repair; (3) Routine System Operation; (4) Seasonal--As Needed; and (5) Operations, Engineering and Maintenance (OEM) Service Contracts. The representative processes above were then placed into the appropriate categories.

Selection of Relevant Input Parameters

The next step in the experimental design was to determine which parameters of the processes would be used as independent variables, or inputs, to the simulation. These parameters include:

- AQL
- p' (process fraction defective)
- Sample size
- Lot size
- Length of simulation
- Statistical distribution of process
- Fault type (explained below).

The term "fault type" refers to the way in which faults are incurred, with faults defined as shifts in the mean operating fraction defective, p'. Four possible fault types were considered: (1) random (spike) shifts; (2) sustained (step) shifts; (3) linear trends; and (4) sinusoidal trends. The case of a stable process (no faults) was also examined. Each of these fault types has associated characteristic parameters. In the random shift situation, the magnitude and frequency of shifts come into play. The frequency of a shift was determined by the rate at which certain process variables shifted from an in-control state to a state at which faults were generated. For example, if a process dealt with floor cleanliness, one process variable of interest would be the mop used, with a "fault-generating" condition being that the mop was dry rather than wet. For fault types 2, 3, and 4, the additional parameters of interest are the magnitude of the process shift and the duration and frequency of the trend. Further explanation and examples of fault types were given in Chapter 2.

Selection of Parameter Levels

Once the important input parameters were enumerated, the values (levels) of these variables were chosen. It is clear that, if many levels were chosen for each variable, the number of tests required for a complete design would rapidly escalate to an unmanageable level. With that point in mind, the following parameter levels were chosen:

<u>AQL</u>: from the documents, AQLs of 1.5, 4, 6.5, and 10 percent were commonly used. The values 1.5 and 6.5 percent were chosen to provide "low" and "high" values and were also the most commonly used in practice.

<u>p'</u>: p' levels were chosen based on the relationship of p' to the AQL. Values of p' that were one-half the AQL, equal to the AQL, and double the AQL were chosen to cover the range of possibilities. The fixed percentages (50 percent below, 100 percent above) were chosen to allow meaningful comparisons between methods at the different AQL values.

<u>Sample sizes</u>: these were set equal to those specified in MIL-STD-105D for the pertinent lot size and AQL, again as a basis for comparing analytical methods.

<u>Lot sizes</u>: determined from process data.

<u>Length of simulation runs</u>: the length of each run was specified as 250 subgroups.

<u>Statistical distributions</u>: due to the binary nature of the processes (good/bad), the statistical distributions were considered to be hypergeometric.

<u>Fault types</u>:

- Random: a total of four combinations were examined: two different shift magnitudes (50 and 100 percent of p') and two frequencies (10 or 40 percent chance of variable shifting to "fault-generating" state).

- Step: runs of five subgroups with 50 or 100 percent magnitude, 10 subgroups with 50, 100, or 200 percent shift in magnitude of p'.

- Linear trend: trends of five subgroups with 0 or 10 between runs and magnitudes of 100 or 200 percent.

- Sinusoid: trends of five subgroups with 100 or 200 percent amplitude, and 10 subgroups with amplitude of 100 percent.

Final Design

Based on the processes chosen earlier as representatives, the parameters selected as most significant, and the corresponding parameter values, the final experimental design appeared as shown in Table 3.

Selection of Relevant Outputs for Evaluating the Methods

The simulation program provides a number of outputs that must be analyzed to compare the different quality evaluation methods. Included are the number of faults, the number of alarms (both true and false), the number of subgroups having p' above the AQL, the number of missed faults (i.e., number of faults minus the number of true alarms), the ratio of true detections to total faults, the total sampling effort, the number of subgroups inspected in tightened, normal, and reduced sampling modes (for acceptance sampling plans using switching rules); and the amount penalized by two different penalty schemes.

The most important outputs were found to be the number of false alarms and the true detection/fault ratio because they yielded the most information for comparative analysis. The number of false alarms is a measure of the producer's risk whereas the true detection/fault ratio allows a direct comparison of the analytical techniques over a variety of process conditions.

Table 3

Experimental Design Parameters

Process No.*	p'	AQL	Lot Size	Sample Size
1	0.0075	0.015	150	20
2	0.015	0.015	200	32
3	0.030	0.015	200	32
4	0.0325	0.065	7665	200
5	0.065	0.065	100	20
6	0.130	0.065	300	50

*The process numbers correspond to the processes obtained from Redstone Arsenal Document #DAAH03-83-C-0049, except for number 4 as noted: 1--clean glass (CLIN 41.8); 2--empty trash (CLIN 41.7); 3--empty trash (CLIN 41.7); 4--accomplish service calls on time (Fort Hood, DAKF-81-B-0059-0002); 5--maintain buildings and structures - roofing (CLIN 24.2); and 6--replace air-conditioner filters (CLIN 41.3). Process 4, with its large lot size, was modeled as a binomial rather than a hypergeometric process.

Simulation Results

The results were divided into subsections according to the type of fault pattern simulated. These results include simulations run with a stable process where p' does not change; a process subject to random "spike" shifts in p'; and processes subject to patterned faults which include step shifts, linear trends, and sinusoidal fault patterns. The results for each of three cases refer to the relationship between p' and the AQL. Each analysis method was studied for p' less than, equal to, and greater than the AQL.

Throughout the evaluation of results, the methods are referenced by number according to the following convention:

Confidence interval approach:

1A--95 percent confidence interval for p' with σ estimated from individual subgroup data

1B--95 percent confidence interval for p' with σ estimated using $\bar{p}$ calculated from the preceding 25 subgroups

1C--95 percent confidence interval for p' with σ estimated using $\bar{p}$ calculated from the preceding 25 stable subgroups: i.e., those where the process is in control (no fault occurred)

2A--95 percent confidence interval for p' centered around $\bar{p}$ with $\bar{p}$ calculated using a moving window of the preceding 25 subgroups (method 2 for stable processes)

2B--95 percent confidence interval for p' centered around p with $\bar{p}$ calculated using a moving window of the preceding 25 stable subgroups (as defined in 1C).

Control chart approach:

3--p-chart with constant limits calculated from first 25 subgroups.

Acceptance sampling approach:

4A--acceptance sampling using MIL-STD-105D without switching rules

4B--acceptance sampling using MIL-STD-105D with proper switching rules.

Stable Processes

With p' less than the AQL (not shown in the figures) and the smaller AQL (1.5 percent), methods 1A and 1B gave many false alarms whereas the other methods gave none. The p-chart, method 3, produced many false alarms in trials where the upper control limit fell below 0.05. This result portrays the sensitivity problem that small sample sizes induce. Because a sample with one defect will be rejected (if the upper control limit is below 0.05) and because the probability of this occurring when p' is 0.015 and n is 20 is quite high (0.13), the underestimation of the process average causes significant problems. When an AQL of 6.5 percent was used, all methods except number 4A performed well. Method 4 gave several false alarms whereas the others did not.

For p' equal to the AQL, methods 2 and 1A performed the best. With the AQL equal to 1.5 percent, methods 1B, 4A, and 4B gave many more false alarms than did other methods. When the AQL was increased to 6.5 percent, the performance was more similar across all methods. This result can be seen clearly in Figure 5 which shows the number of false alarms for each analysis method at each AQL.

As p' became larger than the AQL, method 2 again outperformed all other methods by detecting over 90 percent of the faults that occurred. Between the two acceptance sampling methods, it is clear that use of the switching rules is a significant factor in detecting faults. Figure 6 plots the ratio of true detections to faults when p' was greater than the AQL. Comparing methods 4A and 4B on the graph, it can be seen that MIL-STD-105D with the switching rules, method 4B, was far better than the MIL-STD without switching, 4A, at both AQLs. Method 4B actually detected more than twice as many faults at the smaller AQL. Method 1A was very insensitive at AQL = 1.5 percent. This method caught only one fault out of 250. At the larger AQL, methods 1A, 1B, and 4A performed similarly, catching only 40 percent of the faults.

One other fact that should be pointed out is that all methods worked better at the larger AQL--6.5 percent as opposed to 1.5 percent. This increase in performance is due to more sensitivity at the higher AQL.

Processes Subject to Random "Spike" Shifts

When p' was less than the AQL (not shown in the methods), methods 1B and 1C gave more false alarms than the other methods over all combinations of shift conditions. That is, the results were consistent whether the ratio of state 1 to state 2 probabilities for a transfer function variable was 1.5 or 9.0, or whether the magnitude of the shift in p' when a fault occurs was a 50 percent or 100 percent increase. Method 2B performed well, showing no false alarms. With an AQL equal to 1.5 percent, method 4B, acceptance sampling with switching rules, spent 20 to 30 percent of the time in reduced inspection mode; at the higher AQL, over 95 percent of the time was spent in reduced mode.

For p' equal to the AQL and AQLs as small as 0.015 and 0.065, a shift in p', even a 100 percent increase, was no more than one standard deviation. With shifts this small, it is difficult for any analytical method to detect a fault. In terms of the true detections-to-faults ratio, method 2B performed as expected with shifts of this magnitude. Methods that apparently outperformed 2B by having a larger ratio of detections to faults, such as methods 2A and 4B, also had many more false alarms or a larger number of missed faults. This fact is evident from Figures 7 through 14. Figures 7, 9, 11, and 13 show false alarms for each method under all test conditions for p', equal to AQL, and Figures 8, 10, 12, and 14 show the ratio of true detections to faults. The figures are arranged in pairs, showing the false alarms and the ratio for each of the four sets of test conditions. In Figure 10, the ratio of true detections to faults is higher for method 4B than it is for method 2B at an AQL of 1.5 percent. However, by looking at Figure 9, it is apparent that the number of false alarms is also higher for method 4B than it is for 2B.

Also for this case, when p' was equal to the AQL, the graphs of the true detections-to-faults ratio indicated that the MIL-STD method, using the proper switching rules, outperformed the MIL-STD without switching. This finding reinforces the theoretical notion that use of the switching rules is favorable for catching faults. However, method 4B gave more false alarms than did 4A. This difference in false alarms is greatly reduced at the higher AQL. With an AQL of 1.5 percent, method 4B spent 45 to 65 percent of the time in the tightened inspection mode whereas only up to 33 percent of the time was spent in tightened inspection at the higher AQL. Method 1A was insensitive to shifts in p', detecting few, if any, faults at either AQL and across all random shift conditions. This fact can again be seen in Figures 7 through 14. There was only one instance--a confidence interval for p' using information only from the current subgroup--when method 1A detected more than 5 percent of the faults that occurred. Performance results for the other methods also were consistent over all shift conditions.

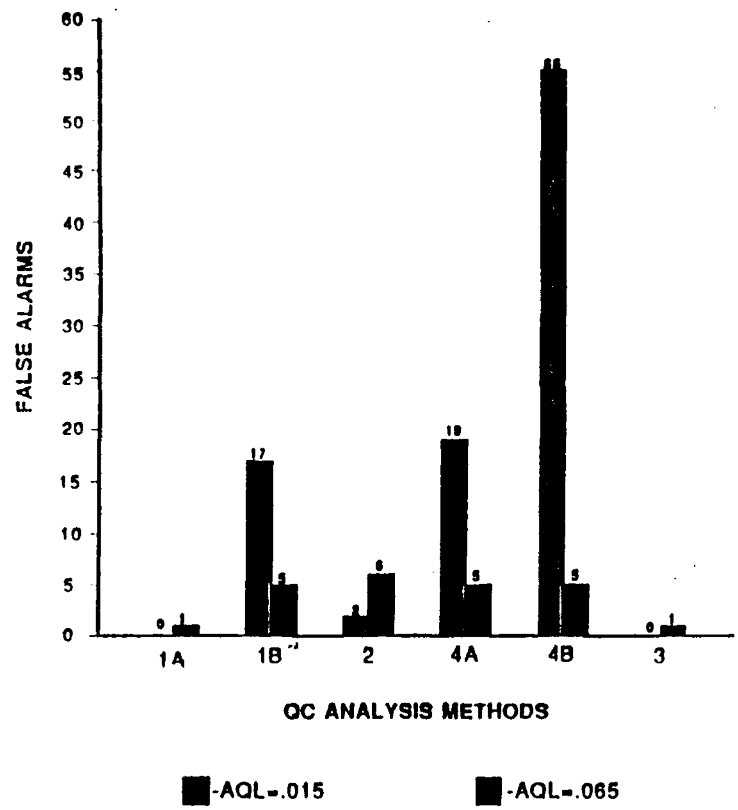

Figure 5. False alarms for a stable process, p' = AQL.

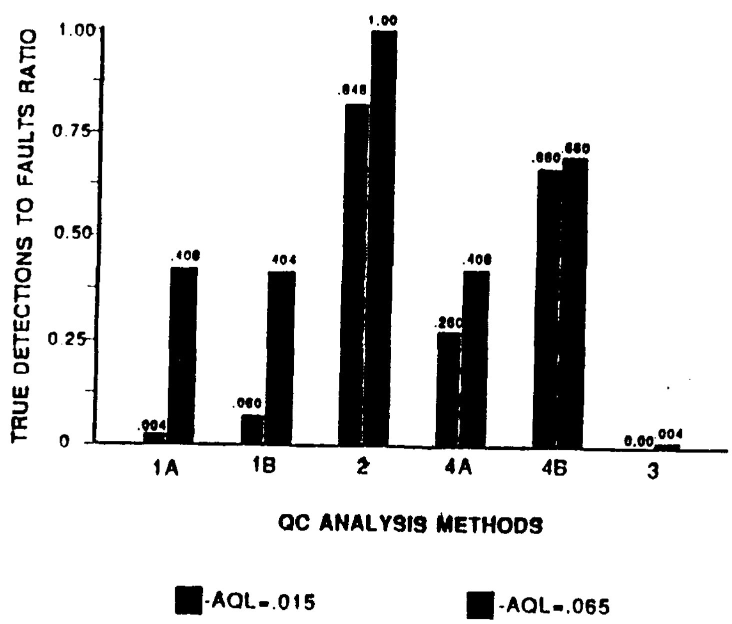

Figure 6. Ratio of true detections and faults, p' > AQL.

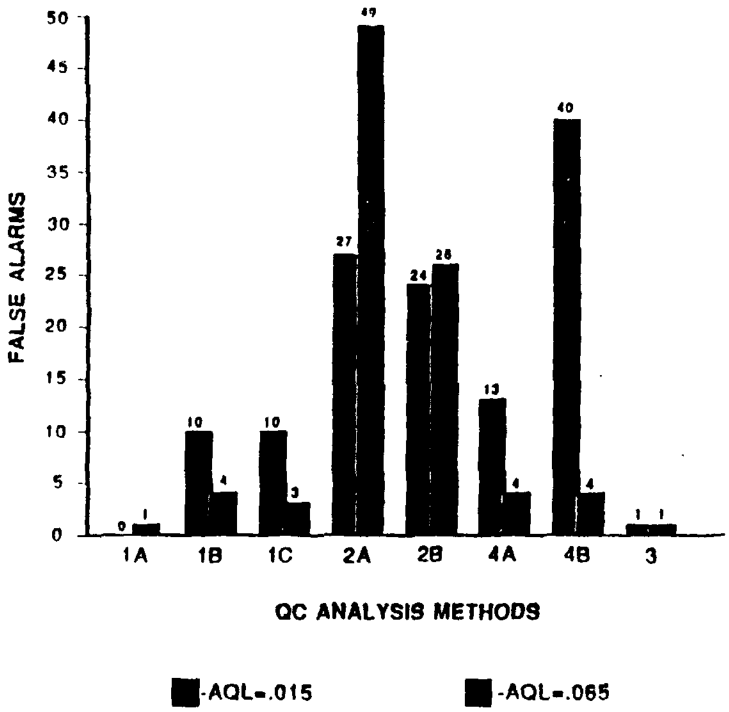

Figure 7. False alarms for process subject to random "spike" shifts, p' = AQL, state probability ratio = 1.5, and shift magnitude = 50 percent.

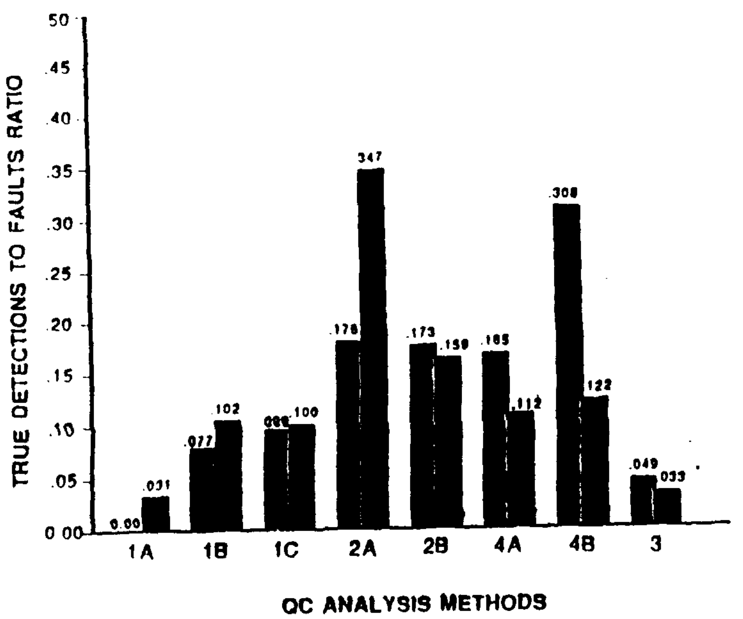

Figure 8. Ratio of true detections to faults for process subject to random "spike" shifts, p' = AQL, state probability ratio = 1.5, and shift magnitude = 50 percent.

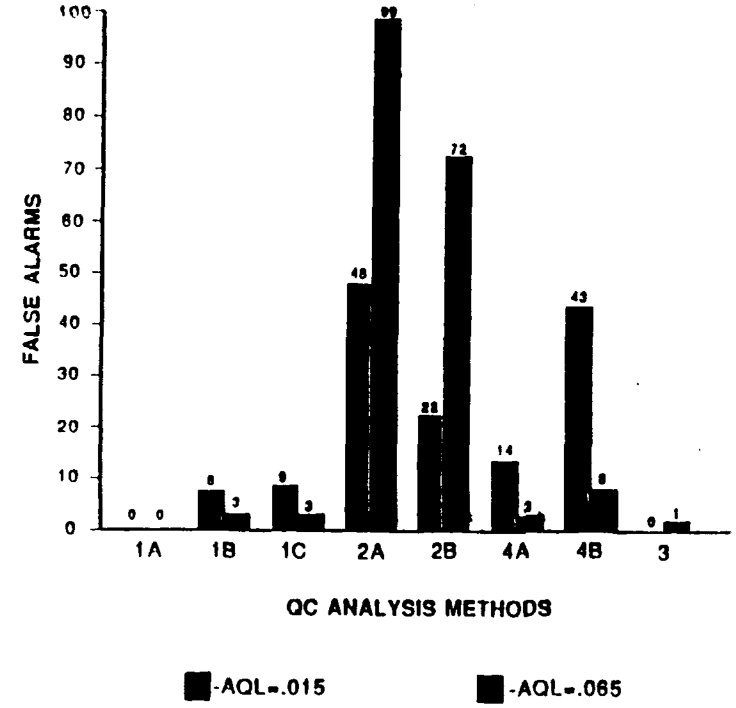

Figure 9. False alarms for process subject to random "spike" shifts, p' = AQL, state probability ratio = 1.5, and shift magnitude = 100 percent.

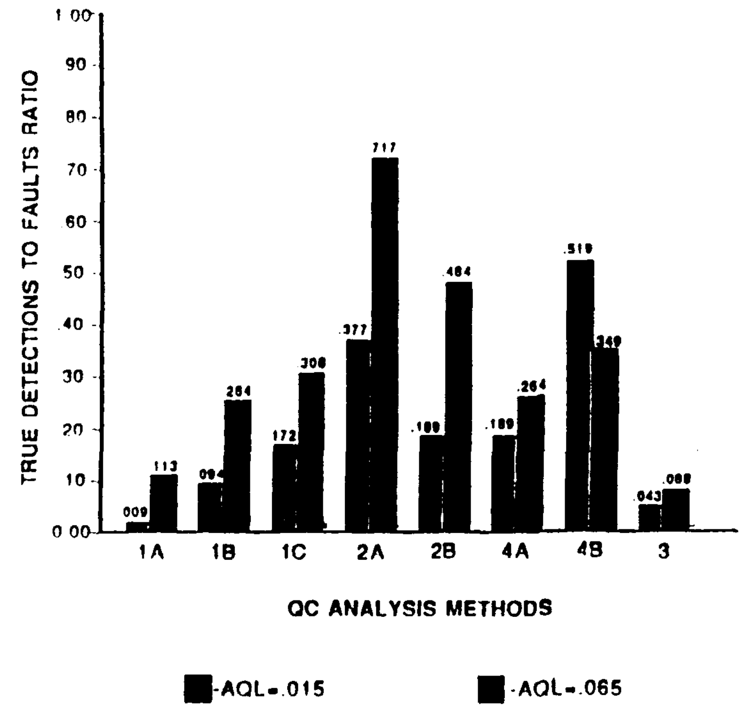

Figure 10. Ratio of true detections to faults for process subject to random "spike" shifts, p' = AQL, state probability ratio = 1.5, and shift magnitude = 100 percent.

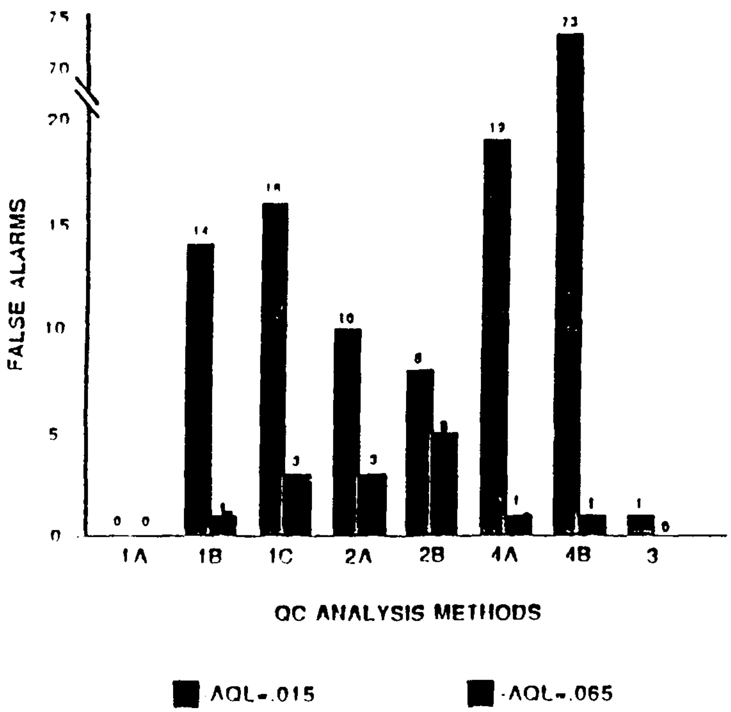

Figure 11. False alarms for process subject to random "spike" shifts, p' = AQL, state probability ratio - 9.0, and shift magnitude = 50 percent.

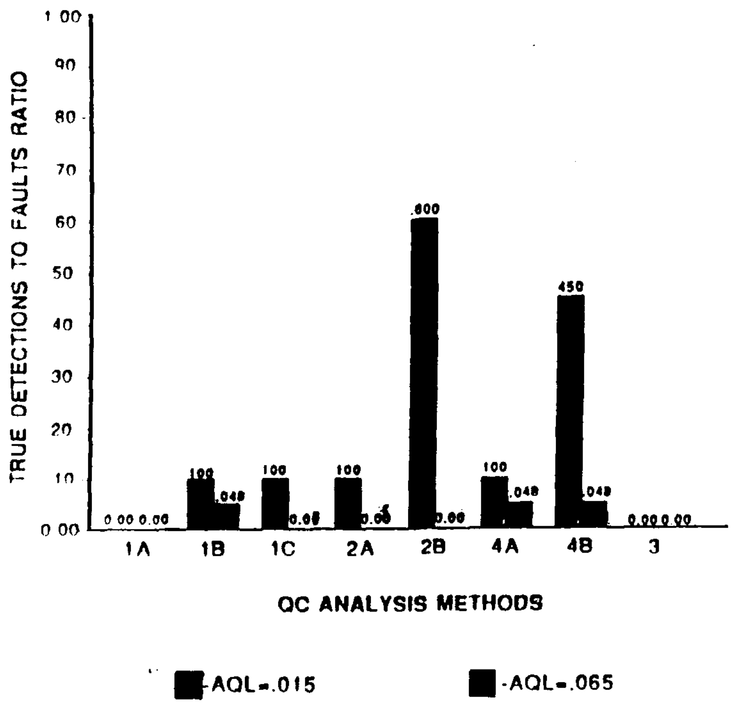

Figure 12. Ratio of true detections to faults for process subject to random "spike" shifts, p' = AQL, state probability ratio = 9.0, and shift magnitude = 50 percent.

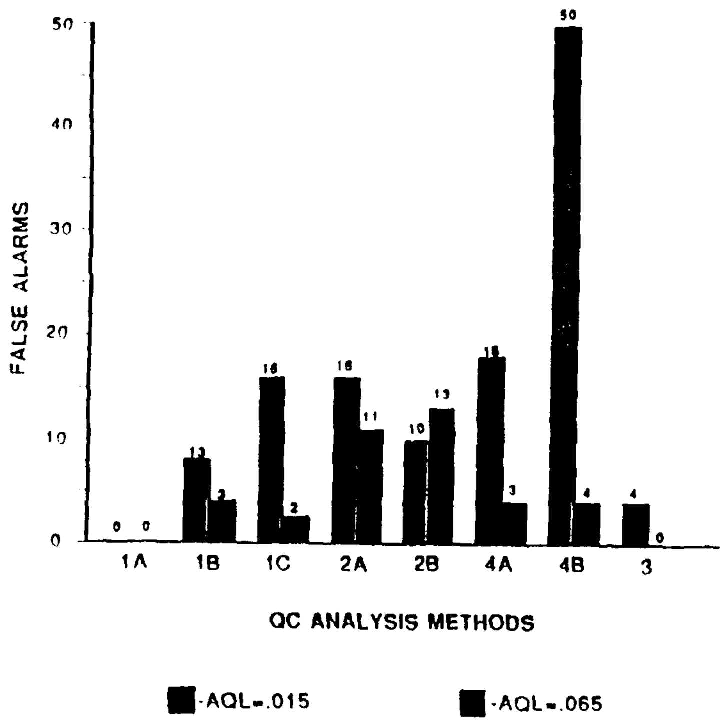

Figure 13. False alarms for process subject to random "spike" shifts, p' = AQL, state probability ratio = 9.0, and shift magnitude = 100 percent.

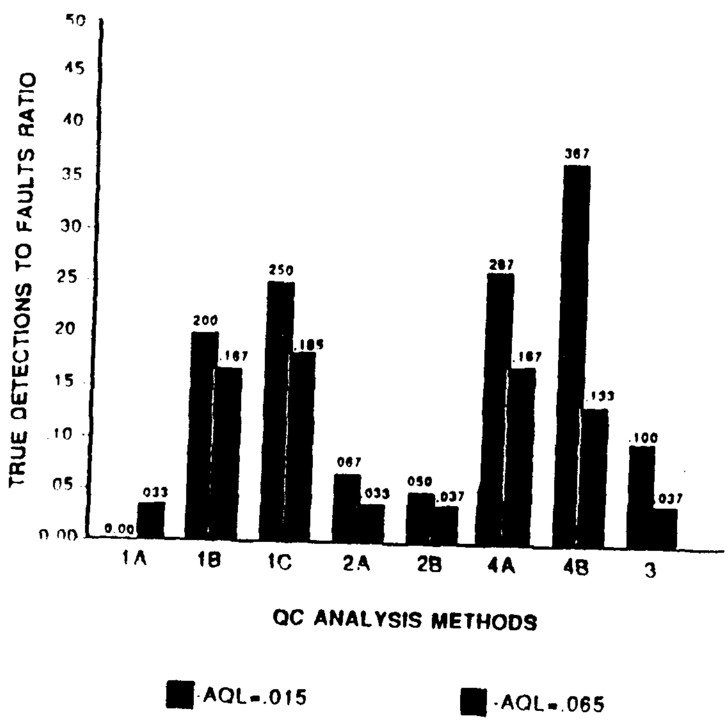

Figure 14. Ratio of true detections to faults for process subject to random "spike" shifts, p' = AQL, state probability ratio = 9.0, and shift magnitude = 100 percent.

The results when p' was greater than the AQL were much the same as in previous cases. Method 2B had the highest percentage of true detections, catching around 95 percent of the faults at the smaller AQL and 100 percent at an AQL of 6.5 percent. Method 4B again outperformed 4A, stressing the need to use the switching rules with acceptance sampling methods. Use of switching rules, as opposed to not using them, in some cases provided over twice as many true detections. This result is apparent in Figures 15 through 18. Since p' was above the AQL, method 4B always spent more than 90 percent of the time in the tightened inspection mode. All of the confidence interval approaches for p' centered around p' (methods 1A, 1B, and 1C) were insensitive to shifts in p', catching less than half the faults in most cases.

Processes Subject to Patterned Faults

Results for this section of the experimental design were derived in part theoretically and partly through simulation. The confidence interval approaches (methods 1A, 1B, 1C, 2A, and 2B) were studied theoretically. It was determined that the results for these methods applied to patterned faults were consistent with those obtained from analysis on random "spike" shifts. The pattern of fault occurrence was not a factor in performance of the analysis method; only the occurrence <u>rate</u> of faults affected the results of the confidence interval approaches.

Methods that were examined by simulation included the p-chart, method 3, and the acceptance sampling method using switching rules, 4B.

Results for the p-chart were consistent over all pattern types. This finding indicates that, as above, it is the rate of occurrence and not the fault pattern which was a factor in the method's performance. For p' below the AQL, the results showed that, as faults occurred more often, the p-chart gave fewer false alarms whereas the ratio of true detections to faults decreased. This condition was true at an AQL of 1.5 percent. At the larger AQL, 6.5 percent, the results were the same except that the detections-to-faults ratio improves by becoming larger.

As p' approached the AQL, p-chart performance remained constant. It was independent of the AQL, the amount of shift in p', and the frequency at which the pattern arose. "Pattern frequency" refers to the number of stable subgroups between fault patterns and the actual length of the pattern itself. As p' increased to become larger than the AQL, the results were similar to the situation where it was equal to the AQL, with one exception: p-chart performance improved with increased pattern frequency.

There were several general results for the p-chart based on the simulation output. First, p-chart performance was better at the higher AQL of 6.5 percent. Also, the performance was better for larger shifts in p' within a given pattern type.

The other method examined through simulation was method 4B, acceptance sampling with switching rules. As with the p-chart method, the performance of method 4B as faults occurred more frequently was consistent over all pattern types. When p' was less than the AQL, the performance was better at AQL = 6.5 percent. At the smaller AQL, more time was spent in normal inspection mode; when the AQL was increased, more time was spent in reduced inspection. This result was due to a difference in σ between the two AQLs.

With p' at the AQL, the overall performance was better for both AQLs because the frequency at which the pattern arose increased. Within a given pattern type, the number of false alarms increased as shifts in p' became larger. There were more false alarms at the lower AQL. However, the ratio of true detections to faults was also higher at this AQL. More time was spent in tightened inspection at an AQL of 1.5 percent than at AQL = 6.5 percent. When p' became larger than the AQL, the performance of method 4B again was better as the frequency of the pattern increased. Also, with this p'/AQL relationship, most of the time was spent in a tightened inspection mode. A general comment that can be made about this method is that the performance in true detections-to-faults ratio is always better for larger shifts in p' within a given pattern type.

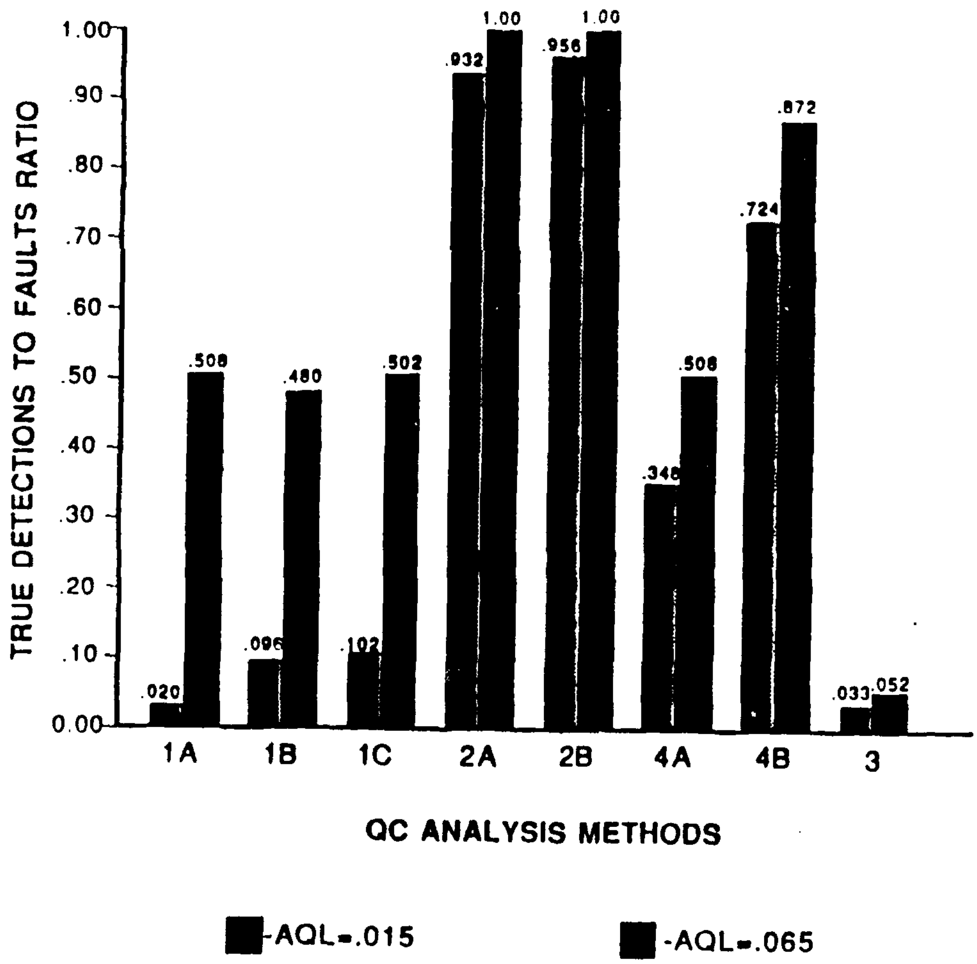

Figure 15. Ratio of true detections to faults for process subject to random "spike" shifts, p' = AQL, state probability ratio = 1.5, and shift magnitude = 50 percent.

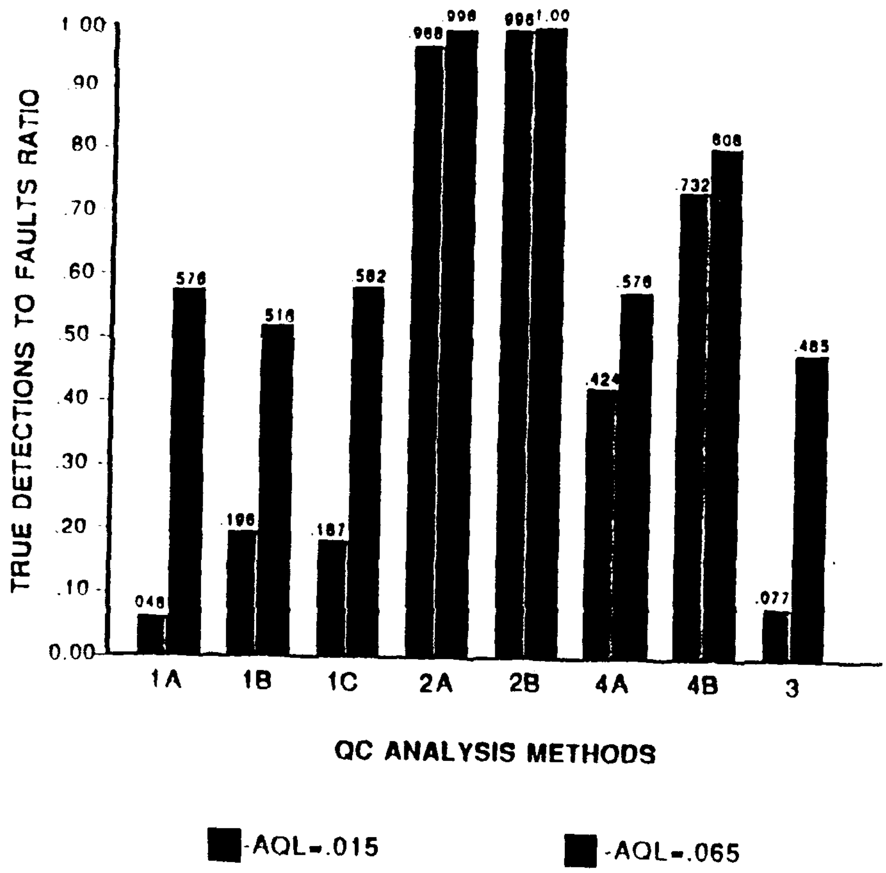

Figure 16. Ratio of true detections to faults for process subject to random "spike" shifts, p' = AQL, state probability ratio = 1.5, and shift magnitude = 100 percent.

Analysis of Results

Results were analyzed over all fault pattern types and p'/AQL relationships (i.e., less than, equal to, and greater than). As noted earlier, each method was compared on the basis of two criteria: occurrence of false alarms and ratio of true detections to faults. The ratio of true detection to faults should be close to one for "good" performance. Table 4 summarizes performance rankings over various process conditions and p'/AQL relationships. Note that from the definitions of faults and false alarms, some rankings are not listed because they do not apply.

When the process is stable and p' equals the AQL, the methods should signal conformance. Confidence interval methods (based on a single subgroup) and p-charting achieved this condition best. When the process is stable and p' is above the AQL, the methods should signal nonconformance. Confidence intervals (based on several subgroups) and MIL-STD-105D with switching rules were the best in this respect.

When the process is unstable, the methods should signal instability and conformance or nonconformance (depending on the value of p' with respect to the AQL). Confidence intervals best meet this objective. Use of confidence intervals is validated by the stability assumption, which is verified by control charting (which performs best in terms of false alarms).

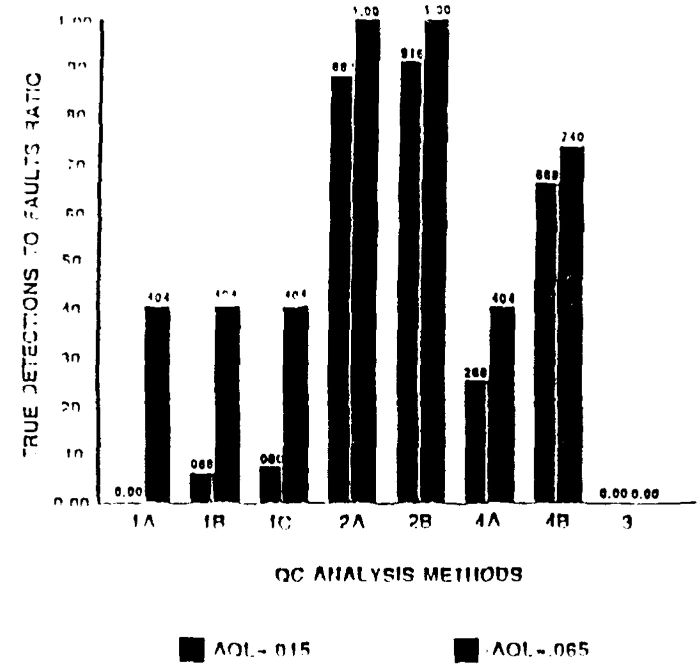

Figure 17. Ratio of true detections to faults for process subject to random "spike" shifts, p' = AQL, state probability ratio = 9.0, and shift magnitude = 50 percent.

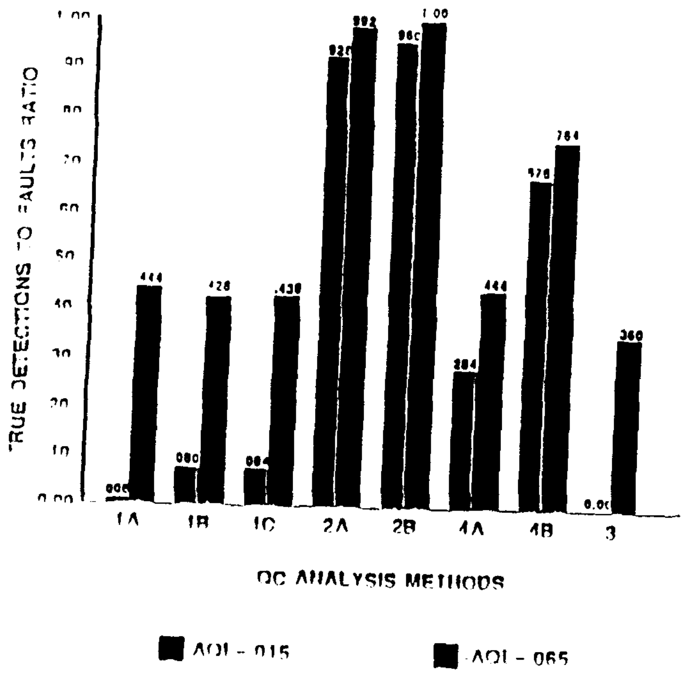

Figure 18. Ratio of true detections to faults for process subject to random "spike" shifts, p' = AQL, state probability ratio = 9.0, and shift magnitude = 100 percent.

Table 4

Performance Rankings of Analytical Techniques

Process Conditions	Value of p'	Value of AQL	Performance*							
			1A	1B	1C	2A	2B	3	4A	4B
Stable	0.015	0.015	1/-	4/-	**	3/-	***	1/-	5/-	6/-
Stable	0.065	0.065	1/-	3/-	**	6/-	***	3/-	3/-	1/-
Stable	0.030	0.015	-/5	-/4	**	-/1	***	-/-	-/3	-/2
Stable	0.130	0.065	-/3	-/5	**	-/1	***	-/-	-/3	-/2
Spike shift	0.015	0.015	1/8	3/6	4/5	-/2	-/3	5/3	6/1	1/7
Spike shift	0.065	0.065	1/7	3/5	3/4	-/1	-/2	3/5	6/3	2/8
Spike shift	0.030	0.015	-/8	-/5	-/6	-/2	-/1	-/4	-/3	-/7
Spike shift	0.130	0.065	-/5	-/7	-/4	-/2	-/1	-/5	-/5	-/8

*The ranking within each cell corresponds to: occurrence of false alarms/ratio of true detections to faults, with a ranking of 1 being best. For an explanation of methods (1A, 1B, etc.) see the text.
**Method equivalent to 1B for this case.
***Method equivalent to 2A for this case.

Specific findings are summarized below.

1. The first point that should be made is that all QC analysis methods performed better at the larger AQL, 6.5 percent. This happens because the values of p' simulated were a function of the AQL. For all simulation runs, p' was either half the AQL, equal to it, or twice the AQL. The magnitude of the shift in p' was either a 50 or 100 percent increase so the amount of shift was dependent on the AQL since p' is a function of the AQL. A larger AQL would produce a greater shift in p', and the larger the shift, the easier it is to detect a fault. This is why, in general, values for the ratio of true detections to faults were higher at an AQL of 6.5 percent than at 1.5 percent. Also, the number of false alarms was smaller at the higher AQL.

2. Each analysis method performed consistently, no matter what type of fault pattern applied. This finding indicates that the type of fault pattern, whether it be a "spike" shift, a step function, a linear trend, or a sinusoid, does not significantly affect the performance of any method. Only the rate of fault occurrence is a factor in determining the best analysis method.

3. The results show clearly that if an acceptance sampling method is to be used (e.g., MIL-STD-105D), the switching rules should be applied properly. Use of the switching rules enhances both consumer and producer protection.

4. The choice of QC analysis method relies on the important question of whether the decision to reject a given lot can be based on information from past history. If the decision can be made using information from only that lot, then there are two choices. The first is to use MIL-STD-105D with the proper switching rules; the second is to adopt a confidence interval approach, method 1A. Although method 1A reduces the incidence of false alarms, it will pick up only behaviors far from the AQL due to a lack of sensitivity.

5. If previous history can be considered in making a decision on a given lot, the following methods should be used simultaneously. A p-chart, method 3, should be used to detect faults as they occur and to establish the true process mean under stable conditions. This method does not compare the process mean to the AQL. For this purpose, a confidence interval approach making use of past history, method 2B, also should be employed. This method is a confidence interval for p' based on a moving $\bar{p}$ calculated using only stable subgroups verified by the p-chart; it will estimate how close the process mean is to the AQL.

The combination of analytical methods is by far the best option. This finding is in agreement with Deming's assessment[8] that, during acceptance sampling, the producer's risk should be guaranteed by an analytical technique using a binomial model (control charts), and the consumer's risk should be guaranteed by an enumerative technique using a hypergeometric model (confidence intervals). The purpose of the analytical test is to discern causes of variability and remove special causes from the system; the enumerative study is done to evaluate what quality the lot has, regardless of why it has it.

[8] W. E. Deming, *Theory of Sampling* (John Wiley and Sons, 1950).

6 IMPLEMENTATION GUIDELINES

General Guidance

The concept of process control, in which a historical perspective of the process behavior is established and used for analysis, can benefit both the producer (contractor) and consumer (installation). The method recommended for DEHs combines two approaches (as discussed in Chapter 5): p chart and confidence interval using switching rules (MIL-STD-105). The purpose of implementing statistical analysis is to provide a structured, cost-effective way to improve the quality of the maintenance function. General guidelines for implementing a process control strategy at an installation are given first, followed by specific steps in the procedure.

Establish the Meaning of Service Quality

Service quality is inversely proportional to the loss imparted to the consumer. The loss is the inconvenience imparted to personnel who use the service or maintain equipment. The definition of quality for a particular service should fit the functional requirements; these requirements should be based on how the service/equipment is used in everyday situations, anticipation of how it might be used in extraordinary situations, and what amount of servicing the installation can fund to achieve the desired level of functionality. There is a tradeoff between exhaustive, but costly inspection requirements and simplistic observation techniques.

Quality per service unit is a direct function of the variability within the process. It is therefore the goal of inspection to estimate this process variability accurately and act accordingly.

Choose the Output(s) of the Service To Be Observed and Evaluated

Often a link must be found between the objective of the service and its observed output quality. For instance, if the objective of the service is to maintain air conditioning equipment, then observable outputs from the service could be the number of breakdowns during the next month, the level of freon added during servicing, and the number of filters replaced improperly. All of these observable outputs correspond to monitoring slightly different objectives; thus, the observable variable must be chosen to correspond to the service/equipment functionality.

Implement QC Window To Assess Process Stability

The QC window is used to observe, control, and improve process quality. It is a generic representation of a closed-loop control function that consists of observation, evaluation, diagnosis, decision, and implementation elements.

For observation, the analyst must choose the sample size and sampling interval. There is no steadfast rule for the sample size used in charting the percent defective; usual sizes range from 20 to 100, depending on the criticality of the service. (Specific sampling plans are suggested in later in **Step-by-Step Guidelines** and in Appendix A.) If the process cannot be out of control very long before irrepairable damage is caused, the sampling interval must be small because even with sensitive statistical methods, there is a lag between fault occurrence and detection. If poor quality is not critical, then the sampling interval can be based more on manpower and cost constraints.

P-chart data are analyzed using two rules: (1) no points shall fall beyond the control limits (or if they fall on the bottom control limit of zero, then this probability must be higher than 0.01) and (2) there must be no runs above or below the mean of length seven or greater. If either of these conditions arises, an out-of-control condition is signaled. Before decisions can be made using the p-chart, control limits must be established. The usual rule of thumb is to collect 20 subgroups before limits are set (which may mean shortening the sampling interval). Ten subgroups is a minimum for establishing limits.

Before a quality history is established, use MIL-STD-105D to evaluate service conformance with the standard. Details are given below in **Step-by-Step Guidelines**.

Correct Out-of-Control Conditions

If an out-of-control condition is met while assessing process stability, notify the contractor so that the fault can be identified and removed from the process. Often the contractor can identify the cause of the problem and joint discussion may lead to a solution. The contractor may use statistical methods such as pareto diagrams, process information sheets, experimental design, and correlative studies in identifying causes of faults.

As faults are identified and removed from the process, the faulted subgroups should be discarded from the calculation of limits because the limits should contain only an estimate of the common cause variability and should not be confused with fault-induced sporadic variability. Also, control limits should be updated occasionally, but no new points should be included in this calculation unless they have been proven to come from the stable process.

Assess Conformance

If process stability is attained, assess process conformance with respect to the AQL. To do so, take the process average from the past five or ten stable subgroups plotted on the p-chart and form a hypergeometric confidence interval for p' based on this process average. If the lower bound of the interval (at 95 or 99 percent confidence) is above the AQL, the process has proven incapable of producing below the AQL. If the interval contains the AQL, then there is no evidence of the process quality not meeting the AQL and sampling should continue as normal.

If the process is found incapable of meeting the AQL requirement, the contractor's methods probably need restructuring (which may involve method improvement, retraining, or equipment change). Once again, if restructuring does take place, the new process must be proven stable before capability can be reassessed.

Step-by-Step Guidelines

Step 1: Determine Sampling Requirements

Contract Requirement. Identify the section of the contract that deals with the contract requirement to be evaluated. List the quality characteristics of the service that will be monitored and establish the exact standards for each characteristic.

Primary Method of Surveillance. Identify the primary method of surveillance and any secondary methods that may be used for diagnostic purposes. Random sampling is the primary evaluation method. Validated complaints may be used only in diagnosis. A validated complaint is any customer complaint identifying a contractor defect as documented by the quality assurance evaluator based on an onsite visit.

AQL. Identify the preestablished AQL within the contract requirements. If the contract does not specify an AQL, establish the percent defective work the contractor should be permitted to supply over a time that would still deem the overall service acceptable.

Amount of Work Performed. Determine a unit of output for each service to be evaluated. This unit should be the same as that defined in the Schedule of Prices.

Lot Size Definition. The number of occurrences of each unit output in a week's time constitutes the lot size (N). If the service is performed on a daily basis, the lot size should be the units completed in a day; if the service is done infrequently and thus may not be performed in any given week segment, the lot size should be the units completed in a month's time. After initial setting of the lot size, keep it constant over time, even if different lots of service take different time periods to complete.

Sample Size. Determine the size of the sample (n) to be used for evaluation. Appendix A gives the required sample sizes for given protection (α and β risks), assuming hypergeometric confidence intervals are used to assess conformance. To determine the sample size requirements, first assign the value of k to be either 5 or 10, the number of consecutive subgroups used to estimate the process average p' in assessing conformance. The lower value of k will produce more sensitivity to changes in conformance but will require that a higher fraction of the lot (n/N) be sampled. As a rule, choose a k of 10 for AQLs less than 0.04, k of 5 for AQLs between 0.04 and 0.10; and k of 3, if desired, for AQLs greater than 0.10.

Next, determine which value of N to look up in Table 5. Basically, N is equal to the midpoint of the lot size ranges used in MIL-STD-105D. These values are also listed in Table 5 for easy access.

Now find the lot tolerance percent defective (LTPD) and beta risk (β). If the process operates at the LTPD, the plan will signify conformance with probability β. The tables in Appendix A show required sample sizes that guarantee a β risk of less than 0.05, 0.10, or 0.15, given an LTPD (larger than the AQL) of 0.05, 0.10, 0.15, or 0.20.

Only AQL, LTPD, β, and N are required to find the necessary sample size, n. Actual α and β risks (for the N shown) are given in the corresponding columns of Appendix A. Conversely, if the actual lot size is larger than the N in the table, protection will be slightly worse than shown. Conversely, if the actual lot size is smaller than the N in the table, protection will be slightly better than shown. If the required n is equal to N in the table, follow this pattern in practice. Example determinations are given below.

Example 1: the value of k is chosen to be 5, AQL is 0.01, LTPD is 0.05, and a β risk of less than 0.05 is desired. For a lot size of 2000, use N equals 2200 (from Table 5). Appendix A reveals that the required sample size (n) is 62. The actual α and β risks for lot size 2200 are 0.001 and 0.048, respectively. Since the actual lot size is smaller than 2200, the actual α and β risks will also be slightly smaller.

Example 2: the value of k is chosen to be 10, AQL is 0.01, LTPD is 0.05, and a β risk of less than 0.05 is desired. For lot size 2500, use N equals 2200. From Appendix A, n is 31. Note that by doubling k (from example 1) the sample size required is halved. The actual α and β risks for lot size 2200 are 0.001 and 0.049, respectively. Since the actual lot size is larger than 2200, the actual α and β risks will be slightly higher.

Example 3: the value of k is 10, AQL is 0.01, LTPD is 0.05, and a β risk of less than 0.05 is desired. For a lot size of 40, use N equals 37. From Appendix A, the required n is 37. Since N equals n, set the actual sample size at the actual lot size, 40. Since the entire lot is sampled, α and β risks are zero.

Table 5

Value of N to Use With Appendix A

Lot Size	N Value
2 to 8	5
9 to 15	12
16 to 20	20
21 to 50	37
51 to 90	70
91 to 150	120
151 to 280	215
281 to 500	390
501 to 1200	850
1201 to 3200	2200

Step 2: Establish Quality History

Sampling Procedure. If samples are already in random order, systematic sampling (sequential) can be used. If not use a random number table (Appendix B). Each sample of size n will be chosen from a lot of size N. Number each unit of service from 1 to N; the purpose is to separate a stream of random digits into groups, with each group representing a service unit number within the lot to be included in the random sample. The number of digits in a group should be equal to the number of digits in a lot, except when the lot size is a power of 10, such as $10^1 = 10$, $10^2 = 100$, and $10^3 = 1000$, in which case the number of digits should be reduced by one. For example, if N = 1000, combine only three digits together and let 000 represent 1000. Let the number of digits chosen be d. Looking at Appendix B, start at a random column and row. Moving in any direction, list the numbers consecutively. Then place a comma between every d digit. Next, cross out all numbers that are greater than N. Obtain n random numbers, where each random number is between 1 and N. These numbers correspond to each unit of service and give you the random sample.

Sampling Frequency. Each lot should be sampled; thus, sampling frequency is a function of lot size. If it is not possible to sample every lot, the frequency should be set as close to this goal as possible.

Process History Requirements. It is necessary to collect M samples of size n before evaluation of stability can begin (M should be greater than or equal to k). The value of M is determined by the lot size definition. If lots are formed daily, choose M to be 25; if lots are formed weekly, choose M to be 20; if lots are formed monthly, choose M to be 10. It is clear at this point why lot sizes should be defined by daily or weekly output.

Step 3: Establish Process Stability

Control Chart Calculations and Plotting. Each of the k samples will be plotted. For each sample, calculate p_i, where:

$$p_i = \frac{\text{Number of defectives in sample i}}{\text{Size of sample i}} \qquad \text{[Eq 6]}$$

Then calculate $\bar{p}$, the centerline of the control chart, by:

$$\bar{p} = \frac{\sum_{i=1}^{M} \text{Number of defective in sample } i}{\sum_{i=1}^{M} \text{Size of sample } i} \qquad \text{[Eq 7]}$$

Since n, the sample size, is constant for the M samples, calculate:

$$UCL = \bar{p} + 3\ \bar{p} = \bar{p} + 3(\bar{p}\ (1-\bar{p}\ )/n)^{1/2} \qquad \text{[Eq 8]}$$

$$LCL = \bar{p} - 3\alpha\bar{p} = \bar{p} - 3(\bar{p}\ (1-\bar{p}\ )/n)^{1/2} \qquad \text{[Eq 9]}$$

If the LCL is less than 0.0, set it at 0.0. The control chart has the value of p on the y axis, and sample number on the x axis. The x axis should be scaled to include at least 50 samples. Control limits should be plotted for x values 1 through k; UCL and LCL should be dashed lines, and $\bar{p}$ should be a solid line. Each value of p should be plotted as a dot and connected between adjacent values.

Control Chart Decisions. The control chart is used to assess stability. For each sample, 1 through k, use these two decision rules to signify instability:

1. If a sample p goes above UCL or below LCL
2. If seven consecutive p values fall above or below the centerline $\bar{p}$.

Diagnosis. If the chart shows stability, proceed to Iterative Analysis below. Any point failing the above decision rules corresponds to a special (local) cause of instability and, as such, its root cause should be eliminated from the process before evaluation proceeds. Remember, diagnosis is situation-dependent. The contractor should be notified so that diagnosis and correction can be performed.

A point exceeding the UCL denotes a shift up in the process mean and its root cause should be determined from analysis of the conditions under which the service took place, i.e., manpower, materials, or methods. A point falling below the LCL denotes either inspection error or a shift down in the process mean. If a downward shift has occurred, identify the reasons to help improve the process in this direction.

If decision rule 2 is true, a sustained shift in the process mean has occurred. Look for process conditions that also changed for a sustained length of time.

Iterative Analysis. As each special cause is identified, recalculate the centerline and control limits (Equations 6 through 9) discarding samples out of control from the calculations. As you recalculate limits and rechart, new points may fail the stability rules. Return to Diagnosis above and continue iteratively until a stable control chart is formed. If at any iteration the number of samples used in the calculations falls below half of k, collect samples from the next k/2 lots and redo all of Step 3.

Step 4: Estimate Service Conformance Prior to Available History

Acceptance Sampling. Until quality history and process stability have been established, nothing can be said about the process' ability to perform at or below the AQL. The only hypothesis that can be tested is whether or not the service (product) conformed to the AQL standard at a single point in time. This service (product) conformance should be estimated using level III inspection (from MIL-STD-105D) starting at the normal inspection levels, with switching rules in force.

Estimation of Service Conformance. Following the steps for acceptance sampling given in Chapter 2 (Military Standard 105D), determine whether the lot (service) is accepted or rejected. If rejected, the process should be investigated to find the cause of the problem and remove it from the system.

Discontinuation of Service Conformance Estimation. Acceptance sampling for evaluating service conformance should be discontinued when k subgroups (lots) have been produced. The value of k refers to the number of consecutive samples used to estimate the process average p' by the statistic $\bar{p}$, as discussed below in Step 5. For AQLs of less than 0.04, use a value of 10 for k. For AQLs between 0.04 and 0.10, use k equals 5. For AQLs higher than 0.10, set k equal to 3.

Step 5: Estimate Process Conformance With Available History

Confidence Interval Estimation. Upon reaching this point, the control chart of the process should reflect stability. After special causes have been identified and removed, each sample will continue to be plotted on the control chart. If the curve violates the stability rules, return to Step 3, Diagnosis. If not, process conformance can be estimated.

To evaluate process conformance at time t, examine the last k (or 5; see Step 1, Sample Size) consecutive lot samples from the stable control chart and calculate $\bar{p}$:

$$\bar{p} = \frac{\sum_{i=t-k+1}^{t} p_i \text{ (from stable process)}}{k}$$

Then form the lower confidence bound (LCB) for the true process percent defective (p'). To do this, choose a producer's risk of approximately 0.025 or 0.005 by setting c equal to 2.0 or 3.0, respectively, and finding:

$$LCB = \bar{p} - c\sigma_{\bar{p}} = \bar{p} - c((\bar{p}\,(1-\bar{p}\,)(1-(n/N))/n)^{1/2}$$

The tables in Appendix A give result: r c = 2.0, which is the recommended value.

Conformance Evaluation. If LCB from the previous step is greater than the AQL, the contractor is not meeting the contract requirements with 97.5 or 99.5 percent confidence (depending on whether c is 2.0 or 3.0). If the process is nonconforming, an appropriate amount may be deducted from the contractor's payment, based on LCB.

Conformance Improvement. The contractor and DEH should work together to determine the reasons for this common cause (system) variability. The system usually must be changed before conformance can be met. For a more in-depth discussion of special and common causes of variability, see Chapter 2.

7 CONCLUSIONS AND RECOMMENDATIONS

Statistical process control technology has been compared with two other QC approaches (acceptance sampling and confidence interval) to determine the feasibility of using process control to develop sampling plans for Army service contracts. The goal is to provide a structured method for assessing the quality of contract work realistically and fairly, given constraints on money and inspectors.

Military installations were surveyed for statistical methods now in use. Two plans are implemented to varying degrees: MIL-STD-105D and the FESA plans. Due to some vagueness in the FESA process, this approach was not studied further. The MIL-STD method incorporates acceptance sampling concepts.

The three approaches were investigated through both theoretical and experimental comparisons. The theoretical assessment produced a unique picture of each approach based on the operating characteristic (OC) curves.

Experimental assessment was through a computer simulation program developed to analyze the effect of these methods on surveillance of real military services that are contracted to outside vendors. The program was designed to simulate stable and unstable processes. Instability can be induced in a process by introducing faults characterized by pattern, size, and rate of occurrence. Various statistics such as the total sampling effort, the ratio of true detections to faults, and the relative occurrence of false alarms were collected as simulation outputs for comparative analysis. Results are as follows:

1. Compared with the MIL-STD plans, at low AQLs, the confidence interval approach had lower consumer and producer risks if k, the number of consecutive subgroups used to estimate the process average, was greater than 10. As the AQL increased, the value of k needed to result in lower risks (compared with MIL-STD plans) decreased towards 2. These comparisons were for equal sampling efforts.

2. All methods studied had greater sensitivity (and thus lower consumer risk) at low AQL values than at high values.

3. The significant factors in fault detection are magnitude and rate of fault occurrence, not the pattern in which faults occur.

4. Failure to use switching rules for MIL-STD plans results in significant increase in both producer and consumer risks.

5. The p-chart is an effective tool in assessing service process stability (constant variability).

This study was limited to developing a basic sampling plan and determining the overall quality of work being performed by a contractor. As a basic study, several issues were not addressed but should be considered in refining the final process. These issues include determining the impact of applying the sampling plan to a project of many tasks, considering inspector allocation and inspection frequency, and designing the QC window elements. Switching rules should also be investigated to identify optimal rules.

Based on these results, a plan was developed to help the Army implement a combination of process control and acceptance sampling methods. This combined procedure will close the gap between risks to the Army and to the contractor. Step-by-step guidance was provided in Chapter 6.

This study supports the following recommendations:

1. The proposed methodology should be field-tested at several installations.

2. While quality history is being established for use in confidence interval and process control methods, service conformance should be evaluated using MIL-STD-105D at level III inspection with switching rules.

3. Process stability should be evaluated using control charts.

4. Process conformance to the AQL standard should be tested using hypergeometric confidence intervals for the process average p', which should be estimated on the basis of quality history.

5. A computer system should be developed which would automatically design the QC methodology. This system would be run by the site quality assurance evaluator and would automatically give guidelines for setting sampling parameters and diagnosing faults, as well as suggestions for process improvement.

Impact on installations expected as a result of implementing these recommendations includes:

- The roles of the contractor and Government will not change. However, cooperation will improve through the flow of process information feedback provided by the Government to the contractor.
- Sampling effort will not increase over its current level.
- Both consumer and producer risks will decrease because of the establishment and use of quality history.
- The contractor will have results available for improved diagnosis of service problems.

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APPENDIX A:

SAMPLE SIZE REQUIREMENTS

To use these tables, the evaluator must determine N, the lot size; k, the number of consecutive subgroups used to estimate the process average p' in assessing performance; LTPD, the lot tolerance percent defective; and β, the beta risk. Chapter 6 provides details.

Sample Size Requirements when $k = 5$, $\beta < 0.05$

For AQL value of = .0100

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	36	0.00000	0.04371
120	56	0.00000	0.04409
215	63	0.00000	0.04624
390	62	0.00001	0.04731
850	62	0.00043	0.04942
2200	62	0.00106	0.04858

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	14	0.00000	0.03877
37	19	0.00000	0.04112
70	17	0.00000	0.04169
120	18	0.00007	0.03511
215	31	0.00000	0.04363
390	31	0.00000	0.04039
850	31	0.00000	0.04375
2200	31	0.00000	0.04550

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	10	0.00000	0.04526
37	12	0.00000	0.04396
70	12	0.00000	0.04227
120	12	0.00001	0.03511
215	12	0.00009	0.04033
390	12	0.00006	0.04243
850	12	0.00021	0.04240
2200	12	0.00032	0.04197

For LTPD = .2000

5	5	0.00000	0.00000
12	9	0.00000	0.01119
20	8	0.00000	0.03415
37	9	0.00000	0.03411
70	9	0.00000	0.02948
120	9	0.00000	0.03309
215	9	0.00002	0.03535
390	9	0.00001	0.03664
850	9	0.00005	0.03750
2200	9	0.00008	0.03795

k = 5, $\beta < 0.05$

For AQL value of = .0250

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	57	0.00000	0.04079
120	76	0.00095	0.04204
215	109	0.00229	0.04475
390	131	0.00179	0.04714
850	156	0.00633	0.04572
2200	156	0.01199	0.04841

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	14	0.00000	0.03877
37	30	0.00000	0.04099
70	28	0.00000	0.04846
120	30	0.00068	0.03740
215	31	0.00137	0.04363
390	31	0.00210	0.04039
850	31	0.00456	0.04375
2200	31	0.00553	0.04550

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	10	0.00000	0.04526
37	20	0.00000	0.04164
70	20	0.00000	0.04909
120	20	0.00002	0.04067
215	21	0.00005	0.03270
390	21	0.00009	0.03605
850	21	0.00022	0.03658
2200	21	0.00029	0.03635

For LTPD = .2000

5	5	0.00000	0.00000
12	9	0.00000	0.01119
20	8	0.00000	0.03415
37	9	0.00000	0.03411
70	15	0.00000	0.03262
120	15	0.00000	0.03985
215	15	0.00000	0.04438
390	15	0.00000	0.04696
850	15	0.00001	0.04867
2200	15	0.00002	0.04957

k = 5, b < 0.05

For AQL value of = .0400

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	70	0.00000	0.00000
120	109	0.00000	0.04724
215	204	0.00000	0.03762
390	312	0.00104	0.04732
850	530	0.01358	0.04816
2200	770	0.01890	0.04859

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	18	0.00000	0.00003
37	30	0.00000	0.04099
70	39	0.00000	0.03681
120	41	0.00018	0.03990
215	54	0.00048	0.04856
390	54	0.00204	0.04635
850	55	0.00613	0.04331
2200	55	0.00724	0.04653

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	16	0.00000	0.04615
37	20	0.00000	0.04164
70	20	0.00000	0.04909
120	20	0.00046	0.04067
215	21	0.00355	0.03270
390	29	0.00026	0.03829
850	29	0.00058	0.03939
2200	29	0.00069	0.03931

For LTPD = .2000

5	5	0.00000	0.00000
12	9	0.00000	0.01119
20	8	0.00000	0.03415
37	15	0.00000	0.03456
70	15	0.00000	0.03262
120	15	0.00003	0.03985
215	15	0.00023	0.04438
390	15	0.00042	0.04696
850	15	0.00070	0.04867
2200	15	0.00076	0.04957

k = 5, b < 0.05

For AQL value of = .0650

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	57	0.00000	0.03874
120	71	0.00050	0.04919
215	108	0.00109	0.04496
390	119	0.01251	0.04890
850	143	0.01570	0.04817
2200	166	0.01353	0.04957

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	16	0.00000	0.04615
37	27	0.00000	0.03853
70	28	0.00120	0.04140
120	35	0.00034	0.04221
215	36	0.00284	0.04351
390	44	0.00229	0.04551
850	44	0.00363	0.04798
2200	44	0.00447	0.04826

For LTPD = .2000

5	5	0.00000	0.00000
12	10	0.00000	0.00067
20	13	0.00000	0.03507
37	15	0.00008	0.03456
70	20	0.00001	0.04922
120	21	0.00026	0.03676
215	21	0.00085	0.04323
390	21	0.00214	0.04691
850	21	0.00278	0.04937
2200	22	0.00491	0.03134

$k = 5$, $\beta < 0.05$

For AQL value of = .1000

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	33	0.00000	0.03440
70	55	0.00013	0.04108
120	63	0.01402	0.03803
215	86	0.00468	0.04743
390	102	0.01138	0.04862
850	110	0.01549	0.04998
2200	118	0.01658	0.04618

For LTPD = .2000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.01034	0.03507
37	20	0.00006	0.04811
70	26	0.00912	0.03453
120	32	0.00568	0.03952
215	33	0.01100	0.03315
390	38	0.00556	0.04931
850	39	0.01004	0.03750
2200	39	0.01106	0.03960

Sample size required when k = 5, b < 0.10

For AQL value of = .0100

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	33	0.00000	0.08547
120	52	0.00000	0.09151
215	58	0.00000	0.09321
390	57	0.00001	0.09112
850	57	0.00022	0.09194
2200	57	0.00056	0.08946

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.08356
37	17	0.00000	0.09667
70	15	0.00000	0.09118
120	16	0.00004	0.07322
215	16	0.00038	0.09023
390	28	0.00000	0.08902
850	28	0.00000	0.09351
2200	28	0.00000	0.09582

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	10	0.00000	0.04526
37	11	0.00000	0.07958
70	11	0.00000	0.07292
120	11	0.00001	0.06083
215	11	0.00006	0.06778
390	11	0.00004	0.07040
850	11	0.00014	0.07008
2200	11	0.00021	0.06932

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.05854
20	7	0.00000	0.09250
37	8	0.00000	0.07595
70	8	0.00000	0.06416
120	8	0.00000	0.06909
215	8	0.00001	0.07212
390	8	0.00001	0.07383
850	8	0.00003	0.07496
2200	8	0.00005	0.07555

k = 5, b < 0.10

For AQL value of = .0250

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12		0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	55	0.00000	0.07680
120	72	0.00042	0.09141
215	103	0.00093	0.09789
390	124	0.00073	0.09709
850	125	0.00829	0.09834
2200	147	0.00536	0.09913

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.08356
37	29	0.00000	0.07557
70	26	0.00000	0.09655
120	27	0.00026	0.09270
215	28	0.00059	0.09713
390	28	0.00095	0.08902
850	28	0.00217	0.09351
2200	28	0.00268	0.09582

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	10	0.00000	0.04526
37	11	0.00000	0.07958
70	19	0.00000	0.07770
120	18	0.00001	0.09652
215	19	0.00002	0.07554
390	19	0.00004	0.08036
850	19	0.00010	0.08046
2200	19	0.00013	0.07962

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.05854
20	7	0.00000	0.09250
37	8	0.00000	0.07595
70	8	0.00002	0.06416
120	14	0.00000	0.07181
215	14	0.00000	0.07750
390	14	0.00000	0.08068
850	14	0.00001	0.08277
2200	14	0.00001	0.08386

k = 5, b < 0.10

For AQL value of = .0400

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	70	0.00000	0.00000
120	107	0.00000	0.09376
215	201	0.00000	0.09987
390	307	0.00044	0.08982
850	480	0.01592	0.09752
2200	672	0.01772	0.09921

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	18	0.00000	0.00003
37	29	0.00000	0.07557
70	37	0.00000	0.07669
120	38	0.00007	0.09190
215	40	0.00331	0.08855
390	51	0.00098	0.08624
850	51	0.00258	0.09476
2200	51	0.00314	0.09907

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	16	0.00000	0.04615
37	19	0.00000	0.07517
70	19	0.00000	0.07770
120	18	0.00018	0.09652
215	19	0.00164	0.07554
390	19	0.00277	0.08036
850	19	0.00428	0.08046
2200	19	0.00458	0.07962

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	.05854
20	7	0.00000	.09250
37	14	0.00000	.07172
70	14	.00000	.06242
120	14	.00002	.07181
215	14	.00013	.07750
390	14	.00024	.08068
850	14	.00040	.08277
2200	14	.00044	.08386

k = 5, β < L 0.10

For AQL value of = .0650

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	46	0.00017	0.09594
120	69	0.00025	0.08488
215	94	0.00220	0.09170
390	104	0.01124	0.09890
850	127	0.01140	0.09667
2200	139	0.01376	0.09370

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	16	0.00000	0.04615
37	26	0.00000	0.07713
70	26	0.00046	0.09766
120	26	0.00303	0.07958
215	34	0.00135	0.08355
390	34	0.00443	0.09298
850	34	0.00613	0.09432
2200	34	0.00712	0.09360

For LTPD = .2000

5	5	0.00000	0.00000
12	10	0.00000	0.00067
20	13	0.00000	0.03507
37	14	0.00004	0.07172
70	14	0.00190	0.06242
120	20	0.00014	0.06251
215	20	0.00049	0.07055
390	20	0.00129	0.07503
850	20	0.00169	0.07797
2200	20	0.00193	0.07949

k = 5, b < 0.10

For AQL value of = .1000

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	32	0.00000	0.09582
70	47	0.00850	0.09408
120	61	0.00681	0.07638
215	77	0.00595	0.08063
390	85	0.01583	0.08835
850	92	0.01528	0.09902
2200	100	0.01581	0.08720

For LTPD = .2000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.01034	0.03507
37	19	0.00003	0.09595
70	25	0.00534	0.06092
120	25	0.01205	0.08109
215	31	0.00469	0.07657
390	31	0.00864	0.08414
850	31	0.01014	0.08904
2200	31	0.01095	0.09155

Sample size required when k = 5, $\beta < 0.15$

For AQL value of = .0100

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	36	0.00000	0.12936
70	31	0.00000	0.12659
120	49	0.00000	0.14702
215	55	0.00000	0.13597
390	53	0.00000	0.14636
850	53	0.00012	0.14479
2200	53	0.00031	0.14021

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.08356
37	16	0.00000	0.13960
70	14	0.00000	0.13018
120	14	0.00002	0.14261
215	15	0.00028	0.12304
390	15	0.00016	0.11418
850	26	0.00000	0.14807
2200	27	0.00000	0.12068

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	9	0.00000	0.10144
37	10	0.00000	0.13571
70	10	0.00000	0.12088
120	10	0.00000	0.10191
215	10	0.00004	0.11061
390	10	0.00002	0.11363
850	10	0.00009	0.11280
2200	10	0.00014	0.11156

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.05854
20	7	0.00000	0.09250
37	8	0.00000	0.07595
70	7	0.00000	0.13018
120	7	0.00000	0.13584
215	7	0.00001	0.13926
390	7	0.00000	0.14117
850	7	0.00002	0.14243
2200	7	000002	0.14308

k = 5, β < 0.15

For AQL value of = .0250

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	53	0.00000	0.12823
120	69	0.00022	0.14880
215	100	0.00057	0.13754
390	98	0.00336	0.14385
850	120	0.00488	0.14704
2200	120	0.00839	0.14366

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.08356
37	28	0.00000	0.12447
70	25	0.00000	0.13138
120	26	0.00019	0.12165
215	27	0.00044	0.12398
390	26	0.00053	0.14324
850	26	0.00124	0.14807
2200	27	0.00205	0.12068

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	9	0.00000	0.10144
37	10	0.00000	0.13571
70	18	0.00000	0.11845
120	17	0.00000	0.14212
215	18	0.00001	0.11074
390	18	0.00002	0.11611
850	18	0.00006	0.11569
2200	18	0.00008	0.11434

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.05854
20	7	0.00000	0.09250
37	8	0.00000	0.07595
70	7	0 00001	0.13018
120	7	0.00100	0.13584
215	7	0.00091	0.13926
390	7	0.00101	0.14117
850	7	0.00151	0.14243
2200	13	0.00000	0.13643

$k = 5$, $\beta < 0.15$

For AQL value of = .0400

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00[illegible]0
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	70	0.00000	0.00000
120	106	0.00000	0.12420
215	200	0.00000	0.12855
390	283	0.002[illegible]4	0.14805
850	453	0.01424	0.14636
2200	601	0.01860	0.14542

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	18	0.00000	0.00003
37	28	0.00000	0.12447
70	25	0.00003	0.13138
120	36	0.00003	0.14892
215	38	0.00193	0.13591
390	38	0.00453	0.12378
850	38	0.00835	0.13073
2200	38	0.00929	0.13424

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	9	0.00000	0.10144
37	18	0.00000	0.12577
70	18	0.00000	0.11845
120	17	0.00011	0.14212
215	18	0.00106	0.11074
390	18	0.00183	0.11611
850	18	0.00288	0.11569
2200	18	0.00309	0.11434

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.05854
20	7	0.00000	0.09250
37	13	0.00000	0.13501
70	13	0.00000	0.11225
120	13	0.00001	0.12305
215	13	0.00007	0.12943
390	13	0.00013	0.13294
850	13	0.00021	0.13524
2200	13	0.00024	0.13643

k = 5, β < 0.15

For AQL value of = .0650

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	45	0.00011	0.13285
120	67	0.00012	0.13664
215	92	0.00132	0.12948
390	102	0.00772	0.13145
850	113	0.01075	0.14542
2200	125	0.01264	0.13516

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	15	0.00000	0.13015
37	25	0.00000	0.13651
70	25	0.00027	0.14183
120	25	0.00197	0.11383
215	25	0.0025	0.13489
390	33	0.00311	0.12280
850	33	0.00437	0.12359
2200	33	0.00512	0 12232

For LTPD = .2000

5	5	0.00000	0.00000
12	10	0.00000	0.00067
20	12	0.00000	0.10174
37	13	0.00002	0.13501
70	13	0.00100	0.11225
120	13	0.00228	0.12305
215	13	0.00407	0.12943
390	13	0.00711	0.13294
850	13	0.00818	0.13524
2200	19	0.00114	0.12097

$k = 5$, $b < 0.10$

For AQL value of = .1000

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	32	0.00000	0.09582
70	46	0.00518	0.14032
120	52	0.01005	0.14950
215	68	0.00716	0.12981
390	76	0.01615	0.12917
850	83	0.01482	0.13764
2200	90	0.01218	0.13979

For LTPD = .2000

5	5	0.00000	0.00000
12	12	0 00000	0.00000
20	12	0.00436	0.10174
37	19	0.00003	0.09595
70	24	0.00299	0.10140
120	24	0.00737	0.12426
215	24	0.00827	0.13698
390	24	0.01298	0.14376
850	30	0.00668	0.12504
2200	30	0.00727	0.12773

Sample Size Requirements when k = 10, $\beta < 0.05$

For AQL value of = .0100

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	33	0.00000	0.03991
120	30	0.00000	0.04127
215	33	0.00028	0.04196
390	32	0.00008	0.04222
850	32	0.00079	0.04077
2200	31	0.00118	0.04974

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.04420
37	17	0.00000	0.04932
70	15	0.00000	0.04061
120	15	0.00000	0.04870
215	16	0.00000	0.03822
390	16	0.00000	0.03317
850	16	0.00000	0.03464
2200	16	0.00001	0.03542

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	10	0.00000	0.01407
37	11	0.00000	0.03350
70	11	0.00000	0.02751
120	10	0.00000	0.04787
215	11	0.00000	0.02353
390	11	0.00000	0.02496
850	11	0.00000	0.02467
2200	11	0.00000	0.02416

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.02526
20	7	0.00000	0.04512
37	8	0.00000	0.03054
70	8	0.00000	0.02215
120	8	0.00000	0.02484
215	8	0.00000	0.02654
390	8	0.00000	0.02751
850	8	0.00000	0.02816
2200	8	0.00000	0.02850

k = 10, b < 0.05

For AQL value of = .0250

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	55	0.00000	0.03742
120	52	0.00780	0.03978
215	80	0.00078	0.04947
390	79	0.00227	0.04484
850	79	0.01122	0.04599
2200	101	0.00291	0.04810

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.04420
37	17	0.00000	0.04932
70	15	0.00000	0.04061
120	15	0.00224	0.04870
215	16	0.00298	0.03822
390	16	0.0343	0.03317
850	28	0.00002	0.03744
2200	28	0.00003	0.03890

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	10	0.00000	0.01407
37	11	0.00000	0.03350
70	11	0.00000	0.02751
120	10	0.00008	0.04787
215	11	0.00015	0.02353
390	11	0.00018	0.02496
850	11	0.00037	0.02467
2200	11	0.00044	0.02416

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.02526
20	7	0.00000	0.04512
37	8	0.00000	0.03054
70	8	0.00000	0.02215
120	8	0.00001	0.02484
215	8	0.00001	0.02654
390	8	0.00001	0.02751
850	8	0.00002	0.02816
2200	8	0.00003	0.02850

k = 10, b < 0.05

For AQL value of = .0400

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	70	0.00000	0.00000
120	108	0.00000	0.03051
215	202	0.00000	0.03570
390	267	0.00091	0.04663
850	377	0.01883	0.04509
2200	483	0.01535	0.04892

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.04420
37	29	0.00000	0.03665
70	26	0.00000	0.04308
120	27	0.00010	0.03850
215	28	0.00226	0.04077
390	28	0.00468	0.03465
850	28	0.00852	0.03744
2200	28	0.00919	0.03890

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	10	0.00000	0.01407
37	11	0.00000	0.03350
70	11	0.00029	0.02751
120	10	0.00105	0.04787
215	19	0.00001	0.02642
390	19	0.00003	0.02919
850	19	0.00007	0.02910
2200	19	0.00008	0.02849

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.02526
20	7	0.00000	0.04512
37	8	0.00000	0.03054
70	8	0.00002	0.02215
120	8	0.00016	0.02484
215	8	0.00057	0.02654
390	8	0.00085	0.02751
850	8	0.00125	0.02816
2200	8	0.00130	0.02850

$k = 10,\ \beta < 0.05$

For AQL value of = .0650

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	46	0.00000	0.04385
120	59	0.00008	0.03348
215	72	0.00134	0.04648
390	82	0.00411	0.04886
850	83	0.01138	0.04758
2200	95	0.01033	0.04073

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	16	0.00000	0.01654
37	19	0.00000	0.02989
70	19	0.00128	0.02901
120	18	0.00196	0.04098
215	26	0.00022	0.04042
390	26	0.00094	0.04547
850	26	0.00138	0.04549
2200	26	0.00165	0.04454

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.02526
20	7	0.00002	0.04512
37	14	0.00000	0.02643
70	14	0.00001	0.01970
120	14	0.00006	0.02466
215	14	0.00017	0.02784
390	14	0.00050	0.02968
850	14	0.00065	0.03092
2200	14	0.00073	0.03156

$k = 10, b < 0.05$

For AQL value of = .1000

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	16	0.00892	0.01654
37	33	0.00000	0.00998
70	40	0.00703	0.04811
120	47	0.00728	0.03337
215	55	0.00505	0.04150
390	63	0.00968	0.03947
850	63	0.01324	0.04244
2200	63	0.01523	0.04237

For LTPD = .2000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00010	0.00880
37	19	0.00000	0.04335
70	19	0.00203	0.03349
120	19	0.00413	0.04375
215	20	0.00871	0.02283
390	20	0.01399	0.02525
850	20	0.01524	0.02688
2200	25	0.00194	0.04444

Sample size required for k = 10, b < 0.10

For AQL value of = .0100

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	31	0.00000	0.07592
120	27	0.00000	0.09873
215	30	0.00012	0.08913
390	29	0.00003	0.08919
850	29	0.00036	0.08537
2200	29	0.00071	0.08091

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.04420
37	16	0.00000	0.08954
70	14	0.00000	0.07366
120	14	0.00000	0.08373
215	15	0.00000	0.06463
390	14	0.00000	0.09317
850	14	0.00000	0.09540
2200	14	0.00000	0.09654

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	9	0.00000	0.05427
37	10	0.00000	0.08144
70	10	0.00000	0.06477
120	10	0.00000	0.04787
215	10	0.00000	0.05446
390	10	0.00000	0.05670
850	10	0.00000	0.05582
2200	10	0.00000	0.05470

For LTPD = .2000

N	n	α	β
5	5	0.00000	0.00000
12	8	0.00000	0.02526
20	7	0.00000	0.04512
37	7	0.00000	0.09940
70	7	0.00000	0.07366
120	7	0.00000	0.07624
215	7	0.00000	0.08104
390	7	0.00000	0.08261
850	7	0.00000	0.08366
2200	7	0.00000	0.08420

k = 10, b < 0.10

For AQL value of = .0250

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	53	0.00000	0.08466
120	49	0.00343	0.08769
215	77	0.00037	0.08732
390	75	0.00095	0.08952
850	75	0.00550	0.08796
2200	74	0.00679	0.09589

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.04420
37	16	0.00000	0.08954
70	14	0.00000	0.07366
120	14	0.00130	0.08373
215	15	0.00183	0.06463
390	14	0.00126	0.09317
850	14	0.00240	0.09540
2200	14	0.00278	0.09654

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	9	0.00000	0.05427
37	10	0.00000	0.08144
70	10	.00000	0.06477
120	10	.00008	0.04787
215	10	.00007	0.05446
390	10	.00008	0.05670
850	10	.00017	0.05582
2200	10	.00020	0.05470

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.02526
20	7	0.00000	0.04512
37	7	0.00000	0.09940
70	7	0.00000	0.07366
120	7	0.00000	0.07824
215	7	0.00000	0.08104
390	7	0.00000	0.08261
850	7	0.00001	0.08366
2200	7	0.00001	0.08420

k = 10, b < 0.10

For AQL value of = .0400

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	70	0.00000	0.00000
120	106	0.00000	0.07991
215	181	0.00000	0.09713
390	242	0.00201	0.09957
850	328	0.01926	0.09767
2200	412	0.01582	0.09443

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	13	0.00000	0.04420
37	28	0.00000	0.08117
70	25	0.00000	0.07222
120	25	0.00003	0.09370
215	26	0.00088	0.09127
390	26	0.00196	0.07805
850	26	0.00379	0.08199
2200	26	0.00414	0.08402

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	9	0.00000	0.05427
37	10	0.00000	0.08144
70	10	0.00012	0.06477
120	10	0.00105	0.04787
215	10	0.00326	0.05446
390	10	0.00464	0.05670
850	10	0.00651	0.05582
2200	10	0.00671	0.05470

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.02526
20	7	0.00000	0.04512
37	7	0.00000	0.09940
70	7	0.00000	0.07366
120	7	0.00005	0.07824
215	7	0.00019	0.08104
390	7	0.00029	0.08261
850	7	0.00043	0.08366
2200	7	0.00045	0.08420

$k = 10,\ \beta < 0.10$

For AQL value of = .0650

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	45	0.00000	0.07532
120	46	0.00079	0.09833
215	59	0.00317	0.09152
390	69	0.00561	0.09029
850	70	0.01364	0.08141
2200	81	0.00908	0.08276

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	15	0.00000	0.08785
37	18	0.00000	0.07064
70	18	0.00059	0.05953
120	17	0.00093	0.07893
215	17	0.00228	0.09323
390	17	0.00544	0.09818
850	17	0.00666	0.09663
2200	17	0.00734	0.09447

For LTPD = .2000

5	5	0.00000	0.00000
12	8	0.00000	0.02526
20	7	0.00002	0.04512
37	7	0.00120	0.09940
70	13	0.00000	0.05410
120	13	0.00002	0.06218
215	13	0.00006	0.06711
390	13	0.00018	0.06988
850	13	0.00024	0.07170
2200	13	0.00028	0.07265

$k = 10,\ \beta < 0.10$

For AQL value of = .1000

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	15	0.00225	0.08785
37	32	0.00000	0.05346
70	39	0.00341	0.08858
120	38	0.00963	0.09522
215	46	0.00595	0.09129
390	54	0.00981	0.07779
850	54	0.01278	0.07955
2200	54	0.01443	0.07814

For LTPD = .2000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	12	.00002	0.05306
37	13	.00025	0.07680
70	18	.00074	0.07825
120	18	.00168	0.09251
215	19	.00405	0.05013
390	19	.00684	0.05374
850	19	.00757	0.05613
2200	19	.00797	0.05737

Sample size required when k = 10, β < 0.10

For AQL valoue of = .0650

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	29	0.00000	0.13297
120	26	0.00000	0.12822
215	28	0.00007	0.14015
390	27	0.00002	0.14023
850	27	0.00020	0.13390
2200	27	0.00041	0.12730

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	12	0.00000	0.11524
37	16	0.00000	0.08954
70	13	0.00000	0.12632
120	13	0.00000	0.13750
215	14	0.00000	0.10534
390	13	0.00000	0.14771
850	14	0.00000	0.09540
2200	14	0.00000	0.09654

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	9	0.00000	0.05427
37	10	0.00000	0.08144
70	9	0.00000	0.13783
120	9	0.00000	0.10612
215	9	0.00000	0.11604
390	9	0.00000	0.11899
850	9	0.00000	0.11699
2200	9	0.00000	0.11483

For LTPD = .2000

5	5	0.00000	0.00000
12	7	0.00000	0.14106
20	7	0.00000	0.04512
37	7	0.00000	0.09940
70	7	0.00000	0.07366
120	7	0.00000	0.07824
215	7	0.00000	0.08104
390	7	0.00000	0.08261
850	7	0.00000	0.08366
2200	7	0.00000	0.08420

k = 10, b < 0.15

For AQL value of = .0250

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	52	0.00000	0.11897
120	47	0.00188	0.13844
215	74	0.00016	0.14417
390	72	0.00047	0.14175
850	72	0.00304	0.13617
2200	71	0.00382	0.14595

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	12	0.00000	0.11524
37	16	0.00000	0.08954
70	13	0.00000	0.12632
120	13	0.00071	0.13750
215	14	0.00107	0.10534
390	13	0.00071	0.14771
850	14	0.00240	0.09540
2200	14	0.00278	0.09654

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	9	0.00000	0.05427
37	10	0.00000	0.08144
70	9	0.00000	0.13783
120	9	0.00003	0.10612
215	9	0.00003	0.11604
390	9	0.00003	0.11899
850	9	0.00007	0.11699
2200	9	0.00008	0.11483

For LTPD = .2000

5	5	0.00000	0.00000
12	7	0.00000	0.14106
20	7	0.00000	0.04512
37	7	0.00000	0.09940
70	7	0.00000	0.07366
120	7	0.00000	0.07824
215	7	0.00000	0.08104
390	7	0.00000	0.08261
850	7	0.00001	0.08366
2200	7	0.00001	0.08420

$k = 10$, $b < 0.15$

For AQL value of = .0400

For LTPD = .0500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	70	0.00000	0.00000
120	105	0.00000	0.11746
215	180	0.00000	0.12245
390	239	0.00107	0.14489
850	303	0.01790	0.14268
2200	364	0.01468	0.14884

For LTPD = .1000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	12	0.00000	0.11524
37	28	0.00000	0.08117
70	24	0.00000	0.11506
120	24	0.00001	0.13858
215	25	0.00052	0.13098
390	25	0.00121	0.11275
850	25	0.00241	0.11708
2200	25	0.00265	0.11929

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	9	0.00000	0.05427
37	10	0.00000	0.08144
70	9	0.00005	0.13783
120	9	0.00044	0.10612
215	9	0.00146	0.11604
390	9	0.00213	0.11899
850	9	0.00305	0.11699
2200	9	0.00316	0.11483

For LTPD = .2000

5	5	0.00000	0.00000
12	7	0.00000	0.14106
20	7	0.00000	0.04512
37	7	0.00000	0.09940
70	7	0.00000	0.07366
120	7	0.00005	0.07824
215	7	0.00019	0.08104
390	7	0.00029	0.08261
850	7	0.00043	0.08366
2200	7	0.00045	0.08420

k = 10, b < 0.15

For AQL value of = .0650

For LTPD = .1000

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	20	0.00000	0.00000
37	37	0.00000	0.00000
70	34	0.00043	0.12820
120	45	0.00046	0.13683
215	58	0.00214	0.12006
390	57	0.01013	0.12759
850	68	0.00759	0.12763
2200	68	0.00996	0.13395

For LTPD = .1500

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	15	0.00000	0.08785
37	17	0.00000	0.14452
70	17	0.00025	0.11244
120	16	0.00040	0.14139
215	17	0.00228	0.09323
390	17	0.00544	0.09818
850	17	0.00666	0.09663
2200	17	0.00734	0.09447

For LTPD = .2000

5	5	0.00000	0.00000
12	7	0.00000	0.14106
20	7	0.00002	0.04512
37	7	0.00120	0.09940
70	12	0.00000	0.12848
120	12	0.00000	0.13858
215	12	0.00002	0.14452
390	12	0.00006	0.14779
850	12	0.00008	0.14993
2200	13	0.00028	0.07265

$k = 10,\ \beta < 0.15$

For AQL value of = .1000

For LTPD = .1500

N	n	α	β
5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	15	0.00225	0.08785
37	32	0.00000	0.05346
70	31	0.01580	0.14895
120	37	0.00531	0.14655
215	38	0.01089	0.13036
390	45	0.00938	0.14752
850	45	0.01171	0.14618
2200	45	0.01299	0.14238

For LTPD = .2000

5	5	0.00000	0.00000
12	12	0.00000	0.00000
20	12	0.00002	0.05306
37	13	0.00025	0.07680
70	12	0.00844	0.12848
120	12	0.01132	0.13858
215	12	0.01029	0.14452
390	18	0.00303	0.10548
850	18	0.00342	0.10847
2200	18	0.00363	0.11001

APPENDIX B:

RANDOM NUMBER TABLE

44	19	15	32	63	55	87	77	33	29	45	00	31
34	39	80	62	24	33	81	67	28	11	34	79	26
74	97	80	30	65	07	71	30	01	84	47	45	89
22	14	61	60	86	38	33	71	13	33	72	08	16
40	03	96	40	03	47	24	60	09	21	21	18	00
52	33	76	44	56	15	47	75	78	73	78	19	87
37	59	20	40	93	17	82	24	19	90	80	87	32
11	02	55	57	48	84	74	36	22	67	19	20	15
10	33	79	26	34	54	71	33	89	74	68	48	23
67	59	28	25	47	89	11	65	65	20	42	23	96
98	50	75	20	09	18	54	34	68	02	54	87	23
24	43	23	72	80	64	34	27	23	46	15	36	10
39	91	63	18	38	27	10	78	88	84	42	32	00
74	62	19	67	54	18	28	92	33	69	98	96	74
91	03	35	60	81	16	61	97	25	14	78	21	22
42	57	66	76	72	91	03	63	48	46	44	01	33
06	36	63	06	15	03	72	38	01	58	25	37	66
92	70	96	70	89	80	87	14	25	49	25	94	62
91	08	88	53	52	13	04	82	23	00	26	36	47
68	85	97	74	47	53	90	05	90	84	87	48	25
59	54	13	09	13	80	42	29	63	03	24	64	12
39	18	32	69	33	46	58	19	34	03	59	28	97
67	43	31	09	12	60	19	57	63	78	11	80	10
61	75	37	19	56	90	75	39	03	56	49	92	72
78	10	91	11	00	63	19	63	74	58	69	03	51
93	23	71	58	09	78	08	03	07	71	79	32	25
37	55	48	82	63	89	92	59	14	72	19	17	22
62	13	11	71	17	23	29	25	13	85	33	35	07
29	89	97	47	03	13	20	86	22	45	59	98	64
16	94	85	82	89	07	17	30	29	89	89	80	98
04	93	10	59	75	12	98	84	60	93	68	16	87
95	71	43	68	97	18	85	17	13	08	00	50	77
86	05	39	14	35	48	68	18	36	57	09	62	40
59	30	60	10	41	31	00	69	63	77	01	89	94
05	45	35	40	54	03	98	96	76	27	77	84	80
71	85	17	74	66	27	85	19	55	56	51	36	48
80	20	32	80	98	00	40	92	57	51	52	83	14
13	50	78	02	73	39	66	82	01	28	67	51	75
67	92	65	41	45	36	77	96	46	21	14	39	56
72	56	73	44	26	04	62	81	15	35	79	26	99
28	86	85	64	94	11	58	78	45	36	34	45	91
69	57	40	80	44	94	60	82	94	93	98	01	48
71	20	03	30	79	25	74	17	78	34	54	45	04
89	98	55	98	22	45	12	49	82	71	57	33	28
58	74	82	81	14	02	01	05	77	94	65	57	70
50	54	73	81	91	07	81	26	25	45	49	61	22
49	33	72	90	10	20	65	26	44	63	95	86	75
11	85	01	43	65	02	85	69	56	89	34	29	64
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